Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry

Yan Liu, Venkatesh Shankar

MANAGEMENT SCIENCE
Vol. 61, No. 10, October 2015, pp. 2514–2535
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

informs
http://dx.doi.org/10.1287/mnsc.2014.2095

The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry

Yan Liu, Venkatesh Shankar
Mays Business School, Texas A&M University, College Station, Texas 77843,
{yliu@mays.tamu.edu, vshankar@mays.tamu.edu}

Product-harm crises (recalls) carry negative product information that adversely affects brand preference and advertising effectiveness. This negative impact of product-harm crises may differ across recall events depending on media coverage of the event, crisis severity, and consumers' prior beliefs about product quality. We develop a state space model to capture the dynamics in brand preference, advertising effectiveness, and consumer response to product recalls; integrate it with a random coefficient demand model; and estimate it using a unique data set containing 35 automobile brands, 193 auto sub-brands, and 359 recalls during 1997–2002. Our results reveal that consumers respond more negatively to product recalls with greater media attention, more severe consequences, and higher perceived product quality. Furthermore, they show that sub-brand advertising effectiveness declines by a greater amount than parent-brand advertising and the decline in effectiveness of the recalled sub-brand's advertising spills over to other sub-brands under the same parent brand.

Keywords: advertising; brand preference; product-harm crisis; Kalman filter; generalized method of moments (GMM)
History: Received March 25, 2013; accepted October 10, 2014, by Pradeep Chintagunta, marketing. Published online in *Articles in Advance* March 26, 2015.

1. Introduction

Firms confront a growing number of product-harm crises. Product-harm crises carry negative product information that over time can have devastating effects on brand preference, advertising effectiveness, market share, and sales. For example, during 2009–2010, Toyota, one of the world's leading automobile manufacturers, announced three major worldwide recalls of nine million vehicles relating to problems with accelerator pedals and floor mats. Toyota later announced that its losses stemming from these recalls totaled as much as $2 billion from lost sales worldwide (*BBC News* 2010). Not surprisingly, their U.S. market share and advertising power plunged during the same period (Szczesny 2010). Other notable product-harm crises include the recalls of Fisher-Price's lead-based paint coated toys in 2007 and Firestone defective tires in 2000. Since 2000, there has been a steady increase in the number of product recalls in the automobile, food, and pharmaceutical industries (Jensen 2011).

Despite the potentially devastating effects of these crises, most firms are inadequately informed and underprepared to handle them (Dawar and Pillutla 2000). Little systematic research exists to help firms develop a better understanding of the market consequences of a product-harm crisis and why and how the damage varies across crises. Existing research can be classified into three broad streams. The first stream investigates the appropriate strategy and managerial action during and after crises using case studies (e.g., Weinberger and Romeo 1989, Smith et al. 1996, Laufer and Combs 2006). The second stream of research uses lab experiments to examine how consumer responses to product-harm crises vary based on their expectations of the concerned brand (Siomkos and Kurzbard 1994, Ahluwalia et al. 2000, Dawar and Pillutla 2000, Lei et al. 2012). Although these two streams provide some guidance to practitioners on how to respond to a crisis, they do not offer insights into the underlying mechanisms of how the affected brands are harmed and what corrective actions may be appropriate under different conditions.

The third stream empirically studies the impact of product-harm crises on performance measures such as sales and market share (Wynne and Hoffer 1976, Crafton et al. 1981, Reilly and Hoffer 1983, Rhee and Haunschild 2006, Van Heerde et al. 2007, Zhao et al. 2011, Van Heerde et al. 2013), marketing effectiveness (Van Heerde et al. 2007, Cleeren et al. 2013, Rubel et al. 2011), stock market performance (Jarrell and Peltzman 1985, Hoffer et al. 1988, Thirumalai and

Sinha 2011, Chen et al. 2009, Yun et al. 2014), and future incidence of recalls (Kalaignanam et al. 2013). Wynne and Hoffer (1976) study short-term effects of automobile recalls on market share and find that recalls have little impact on market share unless the same car model has a series of recalls. In contrast, Crafton et al. (1981) and Reilly and Hoffer (1983) suggest that severe product recall is a significant determinant of demand in the auto industry. With regard to the role of perceived quality of recalled brands, Rhee and Haunschild (2006) suggest that good reputation can be an organizational liability during a product-harm crisis. By contrast, Zhao et al. (2011), based on an analysis of consumer responses to Kraft Foods' peanut butter recall crisis in Australia, suggest that strong brands withstand crises better than weaker brands. Van Heerde et al. (2007) study the same crisis and conclude that it damaged baseline sales and reduced the effectiveness of marketing activities of the recalled brand. Cleeren et al. (2013) empirically analyze recalls of consumer packaged goods in the United Kingdom and show that negative publicity and acknowledgement of blame adversely influence post–crisis advertising spending and price sensitivity. Rubel et al. (2011) model the ex ante advertising decision when envisioning a product-harm crisis and conclude that forward-looking managers should decrease (increase) pre- (post-) crisis advertising expenditures when the likelihood or damage rate of crisis increases.

Although prior research provides a basic understanding and conflicting results on the effects of a product-harm crisis, several important deeper issues remain unexplored. First, not much is known about the long-term impact of a product-harm crisis on brand preference and advertising effectiveness. Product recalls' short-term expenses such as product replacement and consumer compensation may pale in comparison with the decline in consumer brand preference, which can be carried over time, resulting in a long-term impact of product recalls. In addition, product recalls may indirectly affect brand preference by altering advertising effectiveness (Van Heerde et al. 2007, Cleeren et al. 2013). Understanding these long-term effects is critical to the formulation of sound advertising and recall response strategies for the affected brands.

Second, the effects of product recalls on brand preference and demand may vary by important *recall characteristics,* such as media coverage of the recall, recall severity, and the expected quality of the recalled brand. However, little empirical research exists on the impact of these recall characteristics. Consider first, media coverage. During a product-harm crisis, consumers find media reports more trustworthy than the information released by the firm (Jolly and Mowen 1984). On one hand, media can hurt the recalling firm's performance by making the negative event more salient to the public (Ahluwalia et al. 2000). On the other hand, "any news is good news" and media reports may increase the awareness of brands being recalled (Hannah and Sternthal 1984, Berger et al. 2010). These opposing theoretical claims on the effects of media coverage highlight the need for empirical research on these effects. Consider next, recall severity. Consumers may respond more negatively to recalls with more severe potential consequences than to recalls with less severe potential consequences, leading to differential damages to brands with differing recall severity. Indeed, previous research suggests that only severe recalls have significant impact on sales, using simple paired-difference design (Crafton et al. 1981, Reilly and Hoffer 1983). It studies the relationship between recall severity and sales without considering the effects of other variables on sales. It is important to investigate if such differential effects of recall still exist after we control for other recall characteristics, product attributes, and marketing activities. Finally, consider the expected quality of the recalled brand or consumer prior belief about the quality of the recalled brand. On one hand, positive beliefs about the brand could serve as a disadvantage to the brand because recalls violate consumers' previous expectations of highly reputed products (Burgoon and LePoire 1993). On the other hand, consumers' positive beliefs can be an advantage for a brand during a product-harm crisis because of the strong inertia in consumer trust (Aaker et al. 2004). Therefore, firms are interested in knowing whether the negative impact of product recall decreases or increases with consumers' expected quality of the recalled brand.

Third, prior studies primarily focus on *one brand* and a *one-time* crisis event or treat crises as independent events. In reality, firms face multiple product recalls in a given time period. For example, in the auto industry, the average brand was involved in 10 product recalls during the period of 1997–2002. Consumers' negative affectivity associated with previous recall events can be carried over to future periods due to the negative emotional inertia effect (Suls and Martin 2005) and recurrence of prior problems affects people's perceptions of the current problem (Marco and Suls 1993, Zarutra et al. 2005). Indeed, Wynne and Hoffer (1976) find that the impact of recall events is less significant for car models with fewer recalls than for those with multiple recalls, suggesting that consumers' negative responses to prior product recalls can be carried over time. Therefore, product recall characteristics may have a long-term impact on the effect of product recall.

Finally, firms spend on different types of advertising such as parent-brand level (e.g., Toyota) advertising and sub-brand (hereinafter, "nameplate," the corresponding term used in the automobile industry) level (e.g., Toyota Camry) advertising. In response to different product recall events, should firms spend less on advertising the parent brand or the recalled nameplate? The answer to this normative question depends on answers to the theoretical and substantive question: By how much do product recalls diminish the effectiveness of these advertising types? Thus, we seek quantification of the impact of product recall on the effectiveness of parent-brand and nameplate advertising.

In this paper, we address these important research gaps and contribute to the literature by investigating the following important questions. What are the short- and long-term effects of multiple product-harm crises on brand preference? How do recall characteristics, including media coverage of the recall, recall severity, and the expected quality of the recalled brand influence the negative impact of product recall? What effects do product recalls have on the effectiveness of different advertising types? How firms can utilize advertising to better handle a product-harm crisis? To this end, we develop a state space model and estimate it using Kalman filter to capture the dynamics in brand preference that stems from the changes in product recalls and advertising. Our model allows for differential effects of recalls with different recall characteristics. In addition, it incorporates both *direct* and *indirect* effects on brand preference. We integrate the Kalman filter process with a random coefficient demand model based on Berry, Levinsohn, and Pakes (1995) (henceforth, BLP 1995). We estimate our model on a carefully compiled data set in the U.S. passenger car market, comprising 35 parent brands and 193 car nameplates that had a total of 359 recalls during 1997–2002.

Our results reveal that consumers respond more negatively to a product recall when the event attracts larger media attention and when the consequences are more severe. Surprisingly, brand preference and demand decline by a greater amount when the perceived quality of the recalled brand is higher. Although product recalls have significant negative effects on the effectiveness of both parent-brand-level and nameplate-level advertising, nameplate advertising effectiveness declines by a greater amount than parent-brand advertising effectiveness. Thus, firms should spend less on advertising the recalled car nameplate. Furthermore, a product recall on one car nameplate can negatively impact brand preference for all other car nameplates under the same parent-brand name. We also demonstrate through a policy simulation exercise that the firm can improve market share and sales by reallocating spending from nameplate level advertising to parent-brand-level advertising during a product-harm crisis.

Our research makes important contributions to the literature in the following ways. First, it is the first to rigorously establish and explain relationships among product recall, advertising, brand preference, and consumer choice. Second, it provides insights into the long-term impact of product recalls on brand preference and the effectiveness of different advertising types. Third, it offers a deeper understanding of how recall characteristics impact the extent of product harm and a quantification of such an impact. Finally, it investigates the spillover effects of the recall of a sub-brand on the choices and market shares of other sub-brands under the same parent-brand name. These insights enable managers to better understand the impact of a product recall and make more effective advertising decisions to alleviate its damage.

2. Data and Operationalization of Variables

2.1. Data

We study product-harm crises in the U.S. passenger car market.[1] The automobile industry is an ideal context to study product-harm crises because the number of automobile recalls is greater than the number of all other product recalls combined in the United States. (Davidson and Worrell 1992, Chen et al. 2009). Applying our model to this market allows us to effectively analyze the dynamic effects of product-harm crises on brand preference and advertising effectiveness.

We obtain product recall events data from the National Highway Traffic Safety Administration (NHTSA). In the automobile industry, each parent brand typically offers multiple car nameplates. For example, the Toyota brand offers nameplates such as Camry and Corolla. In our data set, there are 35 parent brands and 193 nameplates with 359 product recall events involving about 38.61 million passenger cars. Table 1 provides descriptive statistics of the recall data. The average product recall event involves 107,542 cars.[2] A histogram of the number of units recalled in each product recall event appears in Figure 1. All 35 parent brands and 127 nameplates (out of 193) face at least one recall during the sample period. The average parent brand announces 10 product recalls in the sample with Ford having the largest number (54) of recalls and Mini Cooper having only one product recall during the period of the data. The average car nameplate announces four product recalls in the sample with Dodge Neon having the largest number (14) of recalls. To measure the effects of the

[1] To keep the data manageable for analysis purposes, we exclude SUVs, vans and light trucks, and hybrid cars priced over $110,000.

[2] A product recall event may involve multiple nameplates or car models.

Table 1 Descriptive Statistics of Data

Variable	Mean	S.D.	Max	Min
Product recall variables				
Product recall (PR_{ijt}): units per month	4,869 (63,082)	36,607 (156,844)	2,001,542 (2,001,542)	0 (18)
Severity of the recall ($Severity_{ijt}$): indicator variable[a]	0.68	0.41	1	0
Media coverage of the recall ($Media_{ijt}$): # of articles	1.50	1.88	9	0
Expected quality of recalled brand ($Reliab_{ijt}$): 1–5 scale	3.10	1.24	5.00	1.00
Marketing variables				
Parent-brand-level advertising (A^p_{it}): k$ per month	6,794	8,086	78,832	0
Nameplate-level advertising (A^n_{ijt}): k$ per month	2,419	3,918	41,482	0
CPI-adjusted price (p_{ijt}): k$	26.92	14.93	92.99	8.10
Product attributes				
HPWT: horsepower/lb	0.06	0.01	0.15	0.03
MP$: MPG/$	1.52	0.54	4.28	0.52
Size: length × width in 10^3 square inches	13.07	1.47	17.55	7.95

Notes. S.D., standard deviation. Figures in parentheses denote the descriptive statistics of recalls after deleting all data points with zero recall units.

[a]Severity is equal to one if the recall type is *Increase the chance of crash or fire* and zero if the recall type is *increase the chance of injury when crashing*

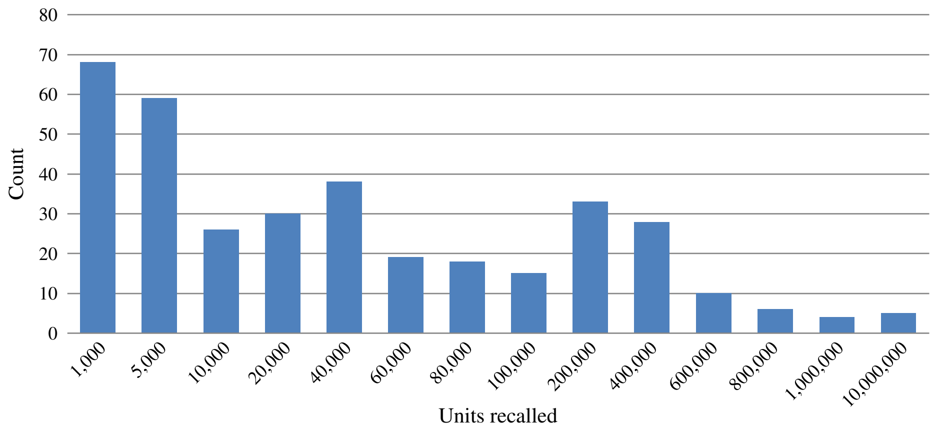
severity of product recall, we classify two severity types based on the consequence of product failure described in the data. Severity type 1 product recalls, which *increase the chance of crash or fire*, involves an immediate safety concern. An example of this type of recall is a recall on cars with a defective brake pedal. Severity type 2 product recalls, which *increase the chance of injury when crashing* also has injury consequences; however, it is conditional on the occurrence of an auto crash that may not be caused by a product defect. Therefore, it has the consequence of failing to protect the passengers during a crash due to malfunctions of key parts such as an airbag or a seatbelt.[3] Of the 359 product recall events in our sample, 67.68% are severity type 1 recalls and 32.31% are severity type 2 recalls.

We obtain print media reports about the recall events from LexisNexis and Factiva. We search across all major media, including the *Wall Street Journal* covered by Factiva. We do an elaborate search on LexisNexis for all articles that mention the name of the firm within the time frame of our data. Specifically, we use two index terms in the search, including "product recall" as a subject and the name of the firm as the company. LexisNexis assigns a relevancy score for each index (e.g., product recall) of each article. We use this score to ensure the articles do indeed discuss the recall events of the firm of interest and that they are not incidental mentions. We identify the articles relevant to the recall events of the firm if the relevancy scores of these two index are 60% or more. We complement these media reports with the *Wall Street Journal* articles obtained from Factiva. Similarly, for Factiva, we use the company tag and subject tag to exclude irrelevant articles. In Table 1, we report the descriptive statistics of the number of media articles about product recall. Table 1 also shows the descriptive statistics of the advertising data. We obtain monthly advertising expenditure data from Ad$pender, a Web-based database that delivers advertising expenditure information on many product categories across all major media. Our advertising expenditure data contain spending in dollars on both *parent-brand-level advertising*, which features the parent brand or varieties of nameplates offered by the parent brand, and *nameplate-level advertising*, which features only one specific car nameplate. In our data, the average automaker spends 41.69% (58.31%) of its advertising budget on parent-brand-level (nameplate-level) advertising.

We obtain U.S. passenger car data during 1997–2002 from Automotive News Market Data Books. This data set contains monthly sales of passenger car nameplates. Table 1 shows the descriptive statistics the car characteristics and price data. We obtain data on car nameplate specific characteristics, such as horsepower (HP), length, weight, and width from the annual issues of *Ward's Automotive Yearbook*. Furthermore, we gather data on miles per gallon (MPG) measuring fuel efficiency of each car nameplate from the U.S. Environmental Protection Agency's website (www.fueleconomy.gov). We collect data on predicted reliability (Reliab) ratings from Consumer Reports. For the price variable, we use annual manufacturer-suggested retail list price (MSRP) data for car nameplates from

[3] Some recalls carry "no consequence of crash or injury." An example of such a recall is one due to defective light bulbs. Our analysis of the differential effects of different types of recalls on brand preference and advertising effectiveness suggests that this recall type has no significant impact in the marketplace. Therefore, we excluded it from our analysis.

Figure 1 (Color online) Histogram of Units Recalled for Each Product Recall Event



Note. Each recall event can involve multiple car nameplates.

Ward's Automotive Yearbook because actual transaction prices are unavailable.

To fully utilize the monthly sales and advertising data, we aggregate the product recall data for each month and each car nameplate. Although all car characteristics and price data are annual, the advertising expenditures and product recall data are monthly.

2.2. Operationalization of Variables

2.2.1. Advertising Variables (A_{ijt}). Based on the description of advertising from Ad$pender, we classify the expenditures on advertising into two types, *parent-brand-level advertising*, A^p_{it-1} and *nameplate-level advertising*, A^n_{ijt-1}. Parent-brand-level advertising refers to advertising that highlights the parent brand. Nameplate-level advertising refers to advertising that features a single car nameplate. Table 1 shows the descriptive statistics of the advertising variables.

2.2.2. Product Recall (PR_{ijt}) and Recall Characteristics (M_{ijt}). To operationalize the product recall variable PR_{ijt}, we use the total number of units (cars) recalled in each month for each car nameplate. We use three recall characteristics, recall severity, media coverage, and expected product quality. As discussed earlier, we classify product recalls into two severity types based on the consequence of product failure described in the data. $Severity_{ijt}$ is a dummy variable that equals one if the recall is severity type 1 and zero otherwise.[4] We use the number of news articles that report the product recall as a measure of media coverage ($Media_{ijt}$), consistent with Hoffman and Ocasio (2001) and Tirunillai and Tellis (2012). Table 1 shows the descriptive statistics of these variables. We measure expected quality of the recalled brand with the expected product reliability rating ($Reliab_{ijt}$) provided by Consumer Reports. Third-party rating is a key component influencing consumer perception of product quality (Levin 2000, Devaraj et al. 2001, Podolny and Hsu 2003). Consumer Reports is one of the most reliable car-rating sources in the United States (Rhee and Haunschild 2006). It uses data reported by actual car owners and provides annual rating on product reliability on a five-point scale.[5] Table 1 presents the descriptive statistics of this variable.

2.2.3. Market Size (MS_t). To calculate the market shares of car nameplates and of the outside alternative, we need to operationalize the market size (MS_t) of passenger cars. Following prior research (e.g., Sudhir 2001, Balachander et al. 2009), we calculate the monthly market size as follows:

$$MS_t = [\text{No. of households}(t) * \text{No. of cars per household}(t)]/[\text{Average age of car} * 12].$$

We obtain annual data on the number of households during 1997–2002 from the *Statistical Abstract of the United States*. According to the Simmons database, the average U.S. household owned 1.49 passenger cars in the sample period. The average age of a car in the United States was 8.85 years during the same period, according to *Ward's Automotive Yearbook*.

2.2.4. Car-Specific Product Characteristics and Environmental Variables (X_{ijt}). Consistent with BLP (1995), Sudhir (2001), and Balachander et al. (2009), we incorporate the following car-specific characteristics: (1) car size (*Size*), which is measured as its length times its width, (2) horsepower (*HPWT*) measured as the ratio of engine horsepower to the weight

[4] In very few exceptional cases, both recall types may happen in the same month for the same nameplate. In such cases, we operationalize severity as the percentage of units (cars) recalled with severity type 1 in each month for each nameplate.

[5] Because we have annual reliability data, the variation is largely cross-sectional. This variable mainly helps us to identify the difference in recall effects across brands rather than over time.

of the car, (3) predicted reliability (*Reliab*) defined in §5.3.2, (4) miles per dollar (*MP$*) measuring fuel efficiency, (5) two-door indicator (*2DR*), and (6) luxury car indicator (*LUX*) based on *Ward's* classification. Table 1 presents the key descriptive statistics of these variables. We also include the following environmental variables: (1) dummy variables for the country/continent of origin of the car brand: U.S., Europe (EUR), and Japan (JAP) (South Korea is the base case) and (2) seasonality indicator variables (Q1, Q2 and Q3) to capture the seasonal effects on demand in different quarters of a year (Q4 is the base quarter).

2.2.5. Price and Income (p_{ijt} and Y_{ht}). Recall that we have only the annual manufacturer-suggested retail list price (MSRP). To get p_{ijt} in Equations (1) and (2), we deflate MSRP to 1997 dollars using the Consumer Price Index (CPI). Therefore, this deflated price, p_{ijt}, varies across months within a particular year only because of the variation in monthly Consumer Price Index. We draw the household income, Y_{ht} for Equation (2) from a lognormal distribution with mean and standard deviation obtained from the Current Population Survey. Because the CPI-adjusted price and household income have little variation in the sample period, we use an average value for the period of the data. Table 1 shows the descriptive statistics of CPI adjusted price variable.

3. Preliminary Analysis

To identify the basic patterns of consequences of product recall in the auto industry data, we use a simple regression model to determine if product recall has an effect on sales and advertising effectiveness. Specifically, we allow sales to be a function of (1) advertising spending, (2) recalls of own car nameplate (e.g., Toyota Camry), (3) interaction of advertising and own nameplate recall, (4) recalls of all other car nameplates under the same parent-brand name (e.g., Toyota Corolla), and (5) control variables including prices, product features, and lagged sales. Thus, we have

$$\begin{aligned}\ln(Sales_{ijt}) = {}& r_0 + r_1\ln(\mathbf{A}_{ijt-1}+1) + r_2\ln(PR_{ijt-1}+1)\\ &+ r_3\ln(PR_{ijt-1}+1)\cdot\ln(\mathbf{A}_{ijt-1}+1)\\ &+ r_4\ln(PR_{i\bar{j}t-1}+1) + r_5\ln(p_{ijt})\\ &+ r_6\mathbf{X}_{ijt} + r_7\ln(Sales_{ijt-1}) + \epsilon_{ijt}, \qquad (1a)\end{aligned}$$

where $Sales_{ijt}$ is the unit sales of nameplate j offered by parent brand i at time t; $\mathbf{A}_{ijt-1}$ is a vector whose elements are the two levels of advertising spending, the parent-brand-level advertising, A^p_{it-1}, and the nameplate-level advertising, A^n_{ijt-1} (that is, $\mathbf{A}_{ijt-1} = [A^p_{it-1}, A^n_{ijt-1}]$); PR_{ijt-1} is the number of units (cars) of name plate j recalled at time $t-1$; $PR_{i\bar{j}t-1}$ is the number of units recalled in nameplates other than j offered by parent brand i at time $t-1$; p_{ijt} is the price; $\mathbf{X}_{ijt}$ is a vector of car characteristics (e.g., size, horsepower), seasonality, and country of origins; $\ln(p_{ijt})$, $\mathbf{X}_{ijt}$, and $\ln(Sales_{ijt-1})$ serve as control variables; r_1 is the coefficient of advertising effectiveness; r_2 captures the effects of product recall on own car nameplate j; r_3 indicates the change in advertising effectiveness due to product recalls (specifically, advertising effectiveness during product recall changes from r_1 to $r_1 + r_3\ln(PR_{ijt-1}+1)$); and r_4 captures the spillover effects of recalls of other nameplates under the same parent-brand name on nameplate j.

The estimation results help us better understand the following pattern in the data (Model 1 in Table 2). First, product recall has a significantly negative impact on own car nameplate sales ($r_2 = -2.37$, $p < 0.01$), consistent with our expectation. Second, product recall has a greater impact on the effectiveness of nameplate-level advertising (-17.48, $p < 0.01$) than that of parent-brand-level advertising (-5.70, $p < 0.01$). Third, the negative effect of a product recall can spill over to other car nameplates under the same parent-brand name ($r_4 = -0.79$, $p < 0.01$).[6]

To test if recall characteristics, including media coverage of the recall, $Media_{ijt}$, recall severity, $Severity_{ijt}$, and the expected quality of recalled brand, $Reliab_{ijt}$, have an impact on consumer response to product recall, r_2, we modify Equation (1a) and estimate a 2SLS model with the interaction effects of recall characteristics and own recall. Specifically, we have

$$\begin{aligned}\ln(Sales_{ijt}) = {}& r_0 + r_1\ln(\mathbf{A}_{ijt-1}+1)\\ &+ (r_2 + \mathbf{r_{2M}}\mathbf{M}_{ijt})\cdot\ln(PR_{ijt-1}+1)\\ &+ r_3\ln(PR_{ijt-1}+1)\cdot\ln(\mathbf{A}_{ijt-1}+1)\\ &+ r_4\ln(PR_{i\bar{j}t-1}+1) + r_5\ln(p_{ijt})\\ &+ r_6X_{ijt} + r_7\ln(Sales_{ijt-1}) + \epsilon_{ijt}, \qquad (1b)\end{aligned}$$

where $\mathbf{M}_{ijt} = |Media_{ijt}, Severity_{ijt}, Reliab_{ijt}|'$. Product recall effects are captured by $r_2 + \mathbf{r_{2M}}\mathbf{M}_{ijt}$ in the aforementioned equation, compared to r_2 in Equation (1a). Thus, $\mathbf{r_{2M}}$ is a parameter vector that captures how recall characteristics $\mathbf{M}_{ijt}$ influences consumer's response to recall. The other terms are as defined earlier. In Table 2, we compare the estimation results of the models with and without recall characteristic effects. Based on Akaike information criterion (AIC), the model with recall characteristic effects (Model 2) fits the data better. Moreover, the coefficients of the interaction terms between each of the three recall

[6] We also find significant negative correlations between sales change and product recall and between nameplate-level advertising and product recall. Details of the correlation analysis are available upon request.

Table 2 Results of Regression Models of Sales

Variable	Model 1 Estimate (S.E.)	Model 2 Estimate (S.E.)
Nameplate-level ad effectiveness: r_1	7.52 (1.96)***	7.75 (1.63)***
Parent-brand-level ad effectiveness: r_1	4.96 (0.80)***	5.21 (01.20)***
Own nameplate's recall: r_2	−2.37 (0.34)***	−2.12 (0.23)***
Other nameplates' recall: r_4	−0.79 (0.19)***	−0.58 (0.08)***
Interaction of own recall and nameplate-level ad: r_3	−17.48 (5.58)***	−18.46 (2.32)***
Interaction of own recall and parent-brand-level ad: r_3	−5.70 (1.03)***	−4.31 (1.06)***
Interaction of own recall and media coverage: $\mathbf{r}_{\mathbf{2M1}}$		−0.05 (0.02)**
Interaction of own recall and severity: $\mathbf{r}_{\mathbf{2M2}}$	−0.16 (0.02)***	
Interaction of own recall and reliability: $\mathbf{r}_{\mathbf{2M3}}$		−0.07 (0.02)***
R^2(AIC)	0.88 (−3,641.65)	0.89 (−3,756.35)

Notes. S.E., standard error. $\ln(PR_{ijt}+1)$ and $\ln(A_{ijt}+1)$ are rescaled by multiplying them by 0.1 and 0.01, respectively. The results of the other covariates are not shown to save space.
**Significant at 0.05; ***significant at 0.01.

characteristics and own recall are significantly negative ($p < 0.05$). This finding indicates that it is important to consider recall characteristics' impact on consumer response to recall.

Although the preliminary analysis suggests that we indeed observe decreases in sales and advertising effectiveness during a product-harm crisis in the automobile industry, it does not capture the richness of the processes or mechanisms by which product recalls affect demand. Therefore, in the following section, we develop a model that incorporates the dynamic and heterogeneous impact of product recall on brand preference, and the effects of product recall on the effectiveness of different advertising types.

4. A Dynamic Model of Product Recall's Impact on Brand Preference and Advertising Effectiveness

We begin with a demand model of consumer choice of a car nameplate from various nameplates offered by different brands. This choice is a function of brand preference, price, and car characteristics. Brand preference is an unobserved stock variable captured as a state space model based on Kalman filtering (KF). This demand model allows us to capture (1) a product recall's direct effect on brand preference and the variation of this effect over time and across nameplates for different recall characteristics and consumer prior beliefs about the brand, and (2) a product recall's effect on advertising effectiveness that indirectly impacts brand preference. This approach is consistent with prior models of advertising and brand preference that use state space models (e.g., Sriram et al. 2006, Naik et al. 2008, Kolsarici and Vakratsas 2010). We then integrate this KF process with a random coefficient demand model based on BLP (1995).

4.1. Demand Model

We consider a market with utility-maximizing consumers or households who shop for a passenger car. We assume that at time t, consumer h chooses from a set of $\Xi_t = \{1, 2, \ldots, J_t\}$ car nameplates offered by a group of brands. The consumer also has the option of not purchasing any of the nameplates at time t, in which case the consumer is considered to be choosing an outside good denoted by $j = 0$. Consistent with prior research on automobile consumer choice (e.g., BLP 1995, Sudhir 2001, Balachander et al. 2009), consumer h maximizes its utility by making the optimal purchase decision as follows:

$$\max_j u_{hijt} = g_{hijt} + \beta_h \mathbf{X}_{ijt} + a\ln(Y_{ht} - p_{ijt}) + \xi_{ijt} + \epsilon_{hijt}, \qquad (2)$$

where u_{hijt} is the indirect utility that consumer h derives from buying car nameplate j of parent brand i at time t, g_{hijt} is consumer h's preference for car nameplate j at time t, Y_{ht} is the income of consumer h, ξ_{ijt} is the unobserved demand shock of nameplate j offered by parent brand i at time t, and ϵ_{hijt} is mean-zero extreme value distributed error. Parameter β is a parameter vector and α is a scalar parameter.[7] The other terms are as defined earlier. The utility of choosing the outside good is

$$u_{h0t} = a\ln(Y_{ht}) + \epsilon_{h0t}. \qquad (3)$$

We let $U_{hijt} = u_{hijt} - u_{h0t}$ and have

$$U_{hijt} = \phi_{ijt} + \mu_{hijt} + \varepsilon_{hijt}. \qquad (4)$$

In the above equation, ϕ_{ijt} is the mean utility that is independent of the consumer's characteristics, μ_{hijt} is

[7] We use the broad term, brand preference for discussion purposes although strictly speaking, it refers to the preference for a sub-brand or nameplate in the model because customer choice is at a nameplate level.

consumer h's deviation from the mean utility. Error ε_{hijt} is a mean-zero extreme value distributed error and $\varepsilon_{hijt} = \epsilon_{hijt} - \epsilon_{h0t}$. Specifically,

$$\phi_{ijt} = g_{ijt} + \beta \mathbf{X}_{ijt} + \xi_{ijt}, \tag{5a}$$

$$\mu_{hijt} = \Delta g_{hijt} + \Delta\beta_h \mathbf{X}_{ijt} + a \ln((Y_{ht} - p_{ijt})/Y_{ht}). \tag{5b}$$

In addition, we assume that the heterogeneity parameter, Δg_{hijt} and $\Delta\beta_h$ are normally distributed with mean zero and variance $\{\sigma_g, \sigma_\beta\}$. We draw $(Y_{ht} - p_{ijt})/Y_{ht}$ from a log-normal distribution with parameters computed from price and income data. The log function of the difference of income and price allows for income effects such as low-income consumers being highly price sensitive. Therefore, in Equation (5b), $\{\sigma_g, \sigma_\beta, \alpha\}$ is a vector of heterogeneity parameters to be estimated.

Assuming ε_{hijt} in Equation (4) to be extreme value distributed, we get the following logit model for the probability of a consumer h buying nameplate j offered by parent brand i at time t.

$$\text{Prob}_{hijt} = \frac{\exp(\phi_{ijt} + \mu_{hijt})}{1 + \sum_\ell \exp(\phi_{i\ell t} + \mu_{hi\ell t})}. \tag{6}$$

4.2. Brand Preference g_{ijt}

Prior research uses a transfer function approach to model the nonstationary process of brand preference g_{ijt} in Equation (5a) and the long-term effects of advertising (Naik et al. 1998, Jedidi et al. 1999, Dube et al. 2005, Sriram et al. 2007). Advertising is perceived as a positive source of information that increases consumer awareness and brand preference. In contrast, a product-harm crisis is perceived as negative product information that adversely impacts brand preference (Dawar and Pillutla 2000). In addition, current product recalls may influence brand preference and demand in the future. To account for the long-term effect of product recall on preference, we modify the classic transfer function of advertising stock (Naik et al. 1998, Jedidi et al. 1999, Dube et al. 2005, Sriram et al. 2007) and develop a preference accumulation model. Specifically, we allow the average consumer's preference for car nameplate j offered by parent brand i at the beginning of time t, g_{ijt} to be an additive function of spending on different advertising types, product recalls, and product recalls of all other car nameplates under the same parent-brand name.

$$\begin{aligned} g_{ijt} = {} & \delta_k^g g_{ijt-1} + q_{ijt-1}^A \ln(A_{ijt-1} + 1) + q_{ijt-1}^R \ln(PR_{ijt-1} + 1) \\ & + q_k^s \ln(PR_{i\bar{j}t-1} + 1) + v_{ijt}. \end{aligned} \tag{7}$$

In this equation, δ_k^g $(0 \le \delta_k^g < 1)$ is the carryover rate of brand type k. The other terms are as defined earlier.[8] To capture potential nonlinear effects, we use the log transformation for both advertising and product recall variables. The term q_{ijt-1}^A is a vector of advertising effectiveness parameters, q_{ijt-1}^R captures the direct effect of product recall on brand preference, and q_k^s measures the spillover effect of product recalls of all other car nameplates under the same parent-brand name. For parsimony and to reduce the number of parameters to be estimated, we assume δ_k^g and q_k^s only vary across brand types and are constant over time.[9] Specifically, we group brands based on brand strength (strong versus weak).[10] We classify a brand as a strong (weak) brand if it's total market share during the sample period is greater (lower) than the average brand's market share. Error v_{ijt} is a normally distributed disturbance, $v_{ijt-1} \sim \mathrm{N}(0, \sigma_v^2)$. Including such a disturbance allows us to capture some unobserved aspects of advertising, such idiosyncrasies (Dube et al. 2005).

The specification of the brand preference in Equation (7) allows us to capture the following aspects of brand preference. First, brand preference carries over time. As a result, the impact of advertising and product recall also carry over time. The extent of this carryover depends on δ_k^g, with a higher value of δ_k^g implying a higher level of carryover and persistence. When $\delta_k^g = 0$, advertising and product recall affect only current brand preference, so such effects are brief. When $0 < \delta_k^g < 1$, a proportion of the damage from the product recall event in the previous period is carried over to the next period. Specifically, the greater the value of δ_k^g, the longer it will take for the market to recover to the level before the adverse event. Second, advertising in the auto industry may feature a parent brand (parent-brand-level advertising) or a nameplate (nameplate-level advertising). Equation (7) allows us to capture the differential effectiveness of these two types of advertising. Third, product recall has a negative impact on brand equity (Dawar and Pillutla 2000), and the damaged brand equity may hurt all car nameplates under the same parent-brand name. Equation (7) allows the effect of recall of one car nameplate (e.g., Toyota Camry) to spill over to other nameplates under the same parent brand and influence consumer choice of these nameplates (e.g., Toyota Corolla).

[8] An alternative way of operationalizing the recall variable is to use a dummy variable to indicate the occurrence of recall events. We estimated a model with dummy recall variables and found the results to be consistent with those from the proposed model. However, the model with dummy recall coding fits worse, indicating that the operationalization of the recall variable as units recalled is more appropriate in our study. The results of this alternative analysis are available upon request.

[9] We are unable to allow the carryover rate to vary over time because of model identification constraints.

[10] We estimated alternative models with different brand type specifications (e.g., domestic versus international, luxury versus nonluxury). The estimation results suggest that there are no significant differences in brand preference carryover rates across country of origin or price segments. The results are available upon request.

4.3. Dynamics in Advertising and Product Recall Coefficients q_{ijt}

During a product-harm crisis, advertising may give less "bang for the buck" when consumers lose trust in the product (Van Heerde et al. 2007). Thus, product recall may have an impact on advertising effectiveness that indirectly influences consumer brand preference. Moreover, consumers' reactions to product recalls may differ by recall characteristics. Prior research that uses lab experiments and survey data suggests that consumer response to product recall is influenced by the following *recall characteristics* (Fiske and Taylor 1991, Siomkos and Kurzbard 1994, Dawar and Pillutla 2000).

(1) *Media Coverage*. Media play an important role with respect to consumer's perception of risk (Siomkos 1999). Moreover, during a product-harm crisis, consumers find media to be a more credible source of information than the manufacturer, so media coverage has a greater influence on consumer perception of danger (Jolly and Mowen 1984). In our data, the mass media report and evaluate 57.44% of the recall events. Wide publicity of product recall events can enhance consumers' negative perceptions of the recalled brand (Siomkos and Kurzbard 1994). As a result, a product recall's negative impact on consumer brand preference may increase with media coverage. However, other studies find support for the idiom, "any news is good news" (Hannah and Sternthal 1984, Berger et al. 2010). The rationale behind this finding is that media reports on the negative event may increase the awareness of the recalled brand whereas the valence of the information may be dissociated from the message contained in the report. In such cases, the positive effect of increased awareness outweighs the negative effects of the media report. Thus, media coverage on recall events may not always be bad for the recalled brand.

(2) *Recall Severity*. According to defensive attribution theory in psychology, when an incident results in a more severe outcome, consumers will attribute a greater blame to the responsible party than when the outcome is less severe (Robbennolt 2000). Therefore, product recalls with more severe potential consequences may result in greater damages to the nameplate than recalls with less severe potential consequences. In our study, on one hand, some severe recalls are due to mechanical problems (e.g., brake failure) that could lead to a crash or a fire and cause immediate harm to the driver. On the other hand, less severe recalls are due to malfunctions of parts that are only used when there is a crash, such as an airbag or a seatbelt. Although these recalls can also result in an injury, it is conditional on the occurrence of a crash that may not be caused by product defect (e.g., reckless driving). Therefore, customers may not respond as negatively for this type of recall.[11]

(3) *Expected Quality of the Recalled Brand*. Consumers' interpretations of objective evidence can vary depending on their prior beliefs or expectations (Oliver and Winer 1987). Previous research in consumer behavior suggests opposing directions of how consumers' prior beliefs on product quality affect their responses to product recalls. On one hand, the more positive consumers' prior beliefs on product quality are, the greater is the extent to which recalls of defective products violate their expectations. Consequently, the negative impact of product recall on brand preference is greater for brands with higher perceived product quality. This speculation is consistent with the theory of expectancy-violation effects (Burgoon and LePoire 1993), which suggests that people respond strongly to objective evidence inconsistent with their prior expectations. On the other hand, consumers' positive beliefs about the brand can be an advantage during a product-harm crisis because of the strong inertia in consumer trust. That is, consumers may refute or ignore negative information on their trusted brands (Aaker et al. 2004). Therefore, brands with higher perceived product quality might be resilient to the negative publicity of product recall. In this study, we empirically test these competing hypotheses and use the expected product reliability rating ($Reliab_{ijt}$) provided by Consumer Reports as the measure of consumer's expected quality of the recalled brand. Consumer perception of product quality is greatly affected by third-party quality ratings (Levin 2000, Devaraj et al. 2001, Podolny and Hsu 2003). This is even more so for consumers' quality judgments on automotive products (Rhee and Haunschild 2006). We expect consumers will more likely form positive prior beliefs toward brands with greater product reliability.[12]

[11] A possible concern in including both recall severity and media coverage is that these two recall characteristics may be highly correlated, so adding media coverage to the model would contribute little additional insights to the model with just recall severity. In our data set, we find significant but weak correlation between these two variables ($\rho = 0.12$, $p = 0.02$). Moreover, there is great variation in media coverage for any given recall severity type (coefficient of variation = 1.27 for severity type 1, coefficient of variation = 1.23 for severity type 2). Therefore, we believe our data allow us to capture media coverage's effect on consumer response to recalls, whereas controlling for the effect of recall severity.

[12] Another potential measure of the expected quality of the recalled brand is product recall frequency. High product recall frequency may damage consumer confidence in the brand, lowering consumer belief about product quality. We estimated a model by including recall frequency and found that recall frequency is an insignificant determinant of consumer response to product recall in automobile industry. A plausible reason is that consumers may not

To model nonstationary advertising effectiveness q^A_{ijt} and consumer response to product recall q^R_{ijt}, we again adopt the parsimonious transfer function approach that has been widely used to study time-varying effectiveness of marketing activities (e.g., price sensitivity, advertising effectiveness) due to different levels of marketing support (e.g., product assortment, distribution breadth) or a market structure break (e.g., new product introduction). For similar applications, see Van Heerde et al. (2004) and Ataman et al. (2010). We write the transfer functions of advertising effectiveness q^A_{ijt} and consumer response to product recall q^R_{ijt}, respectively, as

$$q^A_{ijt} = \delta^A_k q^A_{ijt-1} + q^A_0 + \lambda^A_{ijt} \ln(PR_{ijt} + 1) + \nu^A_{ijt}, \quad (8a)$$

$$q^R_{ijt} = \delta^R_k q^R_{ijt-1} + q^R_0 + \lambda^R_{ijt} \mathbf{M}_{ijt} + \nu^R_{ijt}, \quad (8b)$$

where $\mathbf{M}_{ijt}$ is defined earlier as a vector of recall characteristics and $\mathbf{M}_{ijt} = [Media_{ijt}, Severity_{ijt}, Reliab'_{ijt}]$; δ^A_k and δ^R_k are the carryover rates and $0 \le \delta^A_k(\delta^R_k) < 1$; λ^A_{ijt} measures a product recall's effect on advertising effectiveness; λ^R_{ijt} captures the impact of recall characteristics on consumer response to recalls; ν^A_{ijt} and ν^R_{ijt} are normally distributed error terms; and $\nu^A_{ijt} \sim \mathrm{N}(0, \sigma^2_A)$ and $\nu^R_{ijt} \sim \mathrm{N}(0, \sigma^2_R)$

Equations (8a) and (8b) allow us to capture the following important aspects of advertising effectiveness and recall effects. First, advertising effectiveness may change during a product-harm crisis. Equation (8a) shows the impact of product recall on advertising effectiveness is $\lambda^A_{ijt} \ln(PR_{ijt} + 1)$. Whereas λ^A_{ijt} captures the *indirect effect* of product recall on brand preference by influencing advertising effectiveness, q^R_{ijt} in the brand preference equation (Equation (7)) measures the direct effect of product recall on brand preference. Second, λ^R_{ijt} captures consumers' differential reactions to product recalls with different recall characteristics, including recall severity, media coverage, and the expected quality of the recalled brand. Third, product recall (recall characteristics) may have a long-term effect on advertising effectiveness (recall effects). The term δ^A_k in Equation (8a) represents the carryover rate of a product recall's effect on advertising effectiveness and $0 \le \delta^A_k < 1$. A value close to 0 implies that product recall has a short-term effect. When $\delta^A_k > 0$, such an effect can be more enduring. Similarly, δ^R_k allows us to measure if $\mathbf{M}_{ijt}$ has a short-term (when $\delta^R_k = 0$) or long-term (when $\delta^R_k > 0$) effect on consumer response to product recall. Third, the change in advertising effectiveness not explained by either lagged advertising effectiveness or product recall is captured by the random component ν^A_{ijt}. For example, advertising effectiveness may decrease because of economic downturn (Van Heerde et al. 2013). Similarly, ν^R_{ijt} captures unobserved factors that may influence consumer response to product recall. Therefore, ν^A_{ijt} (ν^R_{ijt}) allows us to recover different potential advertising (recall) parameter paths across nameplates with the data (Van Heerde et al. 2004). In other words, ν^A_{ijt} (ν^R_{ijt}) helps us incorporate both unobserved longitudinal heterogeneity (i.e., changes over time) and unobserved cross-sectional heterogeneity (i.e., changes across nameplates) in advertising effectiveness (product recall effects).

always track recall events over time and may not be aware of the recalls. The results from the estimation of this alternative model are available upon request.

Although a product recall's effect on brand preference q^R_{ijt} changes over time, its impact on advertising effectiveness λ^A_{ijt} may also differ across recall events. Similarly, the effects of recall characteristics λ^R_{ijt} may differ across recall events as well. For example, a negative article on the recall of a strong brand would likely be read more than a negative article on the recall of a weak brand, creating more negative impact on the strong brand. To incorporate such differential effects, we allow λ^A_{ijt} and λ^R_{ijt} to be nameplate and time specific with a random walk formulation that has been used to account for time varying effectiveness of marketing activities. For similar applications, see Ataman et al. (2010) and Van Heerde et al. (2004). Specifically, we let $\lambda_{ijt} = [\lambda^A_{ijt}, \lambda^R_{ijt}]'$ and

$$\lambda_{ijt} = \lambda_{ijt-1} + \nu^\lambda_{ijt}, \quad (9)$$

where ν^λ_{ijt} is a normally distributed disturbance, $\nu^\lambda_{ijt} \sim \mathrm{N}(0, \sigma^2_\lambda)$.

5. Model Estimation and Identification

5.1. Estimation

We recover two vectors of parameters: (1) Vector $\mathbf{\Theta}_1 = [\sigma_g, \sigma_\beta, \alpha]$ in Equation (5b) corresponds to the consumer heterogeneity variables. We refer to it as consumer heterogeneity parameters. (2) Parameters $\mathbf{\Theta}_2 = [\beta, \delta, q_0, \lambda, \theta, q^S, \sigma_v, \sigma_A, \sigma_R, \sigma_\lambda]$ in Equations (5a) and (7)–(9). Vector $\mathbf{\Theta}_2$ corresponds to the parameters in mean utility. We refer to it as mean utility parameters.

For a given set of consumer heterogeneity parameters $\mathbf{\Theta}_1$, we first obtain the mean utility ϕ_{ijt} using contraction mapping, consistent with BLP (1995). Given a set of mean utility parameters $\mathbf{\Theta}_2$ and ϕ_{ijt} from contraction mapping, we use KF process to recover the unobserved state variables, including brand preference, advertising effectiveness and consumer response to product recall, and generate a system of error terms, $\hat{\xi}_{ijt}$ in Equation (5a). We then minimize a quadratic form of these error terms by using the generalized method of moments (GMM) procedure, similar to BLP (1995). The estimation strategy is similar to that of Sriram et al. (2006), Sriram et al. (2007), and Pancras et al. (2012). The details of the estimation algorithm are available upon request.

We now discuss the Bayesian updating process used to recover the unobserved state variables, including brand preference g_{ijt}, advertising effectiveness q^A_{ijt}, consumer response to product recall q^R_{ijt}, a product recall's effect on advertising effectiveness λ^A_{ijt}, and recall characteristics' effect on consumer's response to recalls λ^R_{ijt}, given a set of model parameters. We discretize Equations (7)–(9) and rewrite them in the following matrix form:

$$\begin{bmatrix} g_{ijt} \\ q_{ijt} \\ \lambda_{ijt} \end{bmatrix} = \begin{bmatrix} \delta^g & G_{ijt-1} & 0 \\ 0 & \delta^q & Q_{ijt} \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} g_{ijt-1} \\ q_{ijt-1} \\ \lambda_{ijt-1} \end{bmatrix} + \begin{bmatrix} q^S \ln(PR_{i\bar{j}t-1}+1) \\ q_0 \\ 0 \end{bmatrix} + \begin{bmatrix} v_{ijt-1} \\ \nu^q_{ijt} \\ \nu^\lambda_{ijt} \end{bmatrix}. \tag{11a}$$

In the above equation, $G_{ijt-1} = [\ln(A_{ijt-1}+1) \cdot \ln(PR_{ijt-1}+1)]$, $\delta^q = [\delta^A \ \ \delta^R]$, $q_{ijt} = [q^A_{ijt} \ \ q^R_{ijt}]'$, $Q_{ijt} = [\ln(PR_{ijt}+1)M_{ijt}]'$, $q_0 = [q^A_0 \ \ q^R_0]'$, and $\nu^q_{ijt} = [\nu^A_{ijt} \ \ \nu^R_{ijt}]'$. We assume that the vector of error terms in the previous equation is normally distributed with variance Σ. For simplicity, we assume the elements on the diagonal of variance Σ to be σ^2_v and the off-diagonal elements to be zero. Equation (11a) is the *transition equation* of the KF process. We can rewrite it as

$$\alpha_{ijt} = \Gamma_{ijt-1} \cdot \alpha_{ijt-1} + \Upsilon + \varepsilon_v. \tag{11b}$$

In the above equation, $\alpha_{ijt} = [g_{ijt} \ q_{ijt} \ \lambda_{ijt}]'$ and it is a vector of state variables; and Γ_{ijt-1} is the transition matrix and Υ is the drift vector.

We now link the vector of state variables $\boldsymbol{\alpha}_{ijt}$ to consumer's mean utility ϕ_{ijt}. Given Equations (5a), we can write the relationship between ϕ_{ijt} and state variable α_{ijt} as

$$\phi_{ijt} = [1 \quad 0 \quad 0] \cdot \alpha_{ijt} + K_{ijt} + \xi_{ijt}, \tag{12a}$$

where $K_{ijt} = \beta X_{ijt}$. We assume $\xi_{ijt} \sim \mathrm{N}(0, \sigma^2_\xi)$. Note that although consumer's mean utility ϕ_{ijt} is not observed, it does not have a latent structure. This is because there is a *unique mapping* between unobserved mean utility ϕ_{ijt} and observed market share S_{ijt} (BLP 1995, Sriram et al. 2006). In other words, the contraction mapping algorithm guarantees a *deterministic* relationship between observed market share S_{ijt} and mean utility ϕ_{ijt}. Therefore, mean utility ϕ_{ijt} is a transformation (rather than a stochastic function) of observed market share S_{ijt}, and we can rewrite Equation (12a) as

$$\phi_{ijt} = \psi(S_{ijt}) = Z\alpha_{ijt} + K_{ijt} + \xi_{ijt}, \tag{12b}$$

where $\psi(\cdot)$ indicates the contraction mapping process and $Z = |1 \quad 0 \quad 0|'$. We term the previous equation as the observation equation of the KF process.

We now discuss the initial condition of state variables at time $t = 0$, $\mathbf{a}_{ij0} = [g_{ij0} \ \ q_{ij0} \ \ \lambda_{ij0}]'$. For parsimony and due to data constraints, we assume that the nameplate-specific initial preference g_{ij0} is constant across all nameplates offered by the same parent brand and estimate parent-brand-specific initial preference g_{i0} rather than nameplate-specific initial preference g_{ij0}. The prices are at the annual level. Given our relatively short data window of six years, the price variation in our data is primarily cross-sectional. Consequently, we face an identification problem when we include nameplate-specific initial preference. Therefore, we estimate the parent-brand-specific initial preference parameter g_{i0}. For identification purpose, we set g_{i0} of a base parent brand to be zero. Furthermore, we assume that at time zero, all brands have recovered from the negative impact of any previous product recall. Therefore, the initial advertising effectiveness q^A_{ij0} is set to be the fixed mean $q^A_0/(1-\delta^A)$ around which q^A_{ij0} fluctuates when there is no product recall. Similarly, the initial value of product recall coefficient q^R_{ij0} is $q^R_0/(1-\delta^R)$ with $M_{ij0} = 0$. The initial value of λ_{ij0} is a set of parameters to be estimated. By adding the parameter of the error term σ_ξ in Equation (12a), the initial brand equity parameter g_{i0}, and the parameter of λ_{ij0}, we now rewrite sub-brand level parameters as $\boldsymbol{\Theta}_2 = \{\beta, \delta, q_0, \lambda, \theta, q^S, \sigma_v, \sigma_A, \sigma_R, \sigma_\lambda, \sigma_\xi, g_{i0}, \lambda_{ij0}\}$.

Given the *transition equation* (Equation (11b)) and the *observation equation* (Equation (12b)), we can compute the estimated unobserved demand shock $\hat{\xi}_{ijt}$ using a Bayesian updating process (West and Harrison 1997). By minimizing a quadratic form of these error terms, $\hat{\xi}_{ijt}$, we obtain the model parameters with a GMM procedure similar to BLP (1995).

5.2. Identification and Endogeneity

In this subsection, we discuss the issues of model identification and potential endogeneity of key variables, such as price, advertising, product recall, product attributes, and media coverage.

5.2.1. Model Identification. The identification of consumer heterogeneity depends on the substitution patterns among brands. As the variance of consumers' random tastes for product characteristics increases, similar products (in the product characteristics space) become better substitutes (BLP 1995). We refer the readers to BLP (1995) and Nevo (2001) for further details on the identification of heterogeneity parameters.

We now discuss the identification of effects of the key variable, namely, product recall. In our model, product recall has both direct and indirect effects on preference and consequently, market share. The identification of the direct and indirect effects (through advertising effectiveness) of product recall on reference is analogous to the identification of the main effect of product recall and the interaction effect of product recall and advertising in the simple regression model discussed in §3. The direct effect of product recall is identified based on market share changes during a product-harm crisis, after controlling for advertising spending and other factors that may affect market share. The identification of the indirect effect of product recall on preference is based on the difference in the movement of market share because of a shock in advertising spending with and without product recall. Furthermore, a product recall's effect on brand preference can change over time because of different recall characteristics. The change in product recall effect over time is identified based on the extent to which a product recall induces market share changes given different recall characteristics, after controlling for other potential factors that might affect market share. The spillover effect of product recall on preference is identified based on market share changes during the recall events of the nameplates under the same parent-brand name, after controlling for the recall of own nameplate. We have 457 product recall events with different magnitudes and different severity types in the sample period. Our data reveal significant variation in both product recall and advertising spending over time and across nameplates. Table 1 provides the standard deviations for the recall data and advertising data. Overall, these data suggest that there is enough variation to isolate the effects of product recalls.

Furthermore, we provide the analytical proof of state space model identification in Appendix B. The mean utility parameters are identified if there exists no other system observationally equivalent to the one specified in Equations (11b) and (12b) (Harvey 1991, Bass et al. 2007). Our state space model (KF process) is defined by quadruples $N = \{Z, \Gamma, \xi, \varepsilon_v\}$. We first construct an observationally equivalent system, $N_1 = \{Z_1, \Gamma_1, \xi_1, \varepsilon_{v1}\}$, so that both systems N and N_1 ensure the recovery of state variables α_t, given the knowledge of observed market share S_t, and produce the same forecasted market share (West and Harrison 1997). We obtain the equivalent system N_1 by replacing the state variable α_t in Equations (11b) and (12b) with $\alpha_{1t} = L\alpha_t$, where L is a $n \times n$ nonsingular matrix and n is the dimension of α_t. This leads to $Z_1 = ZL^{-1}$, $\Gamma_1 = L\Gamma L^{-1}$, $K_1 = LK$, and $\xi_1 = L\xi L'$. Because this transformation ensures that the system N_1 is equivalent to our system N, it is sufficient to show that our KF process is identifiable if all transformations are precluded except L is an identity matrix. Detailed proof of L being an identity matrix in our model is available upon request. Bass et al. (2007) employ a similar approach to prove the identification of a state space model of advertising effectiveness. Moreover, to further demonstrate the identification of the proposed model, we estimated the model with simulated data. The results reveal that the proposed model and estimation algorithm can recover the true parameters with a high level of accuracy. Details of the simulation analysis are available upon request.

5.2.2. Exogeneity of Product Recall and Product Features. In the auto industry, manufacturers are required to notify the NHTSA and consumers and execute a recall when there is a safety problem. According to the National Traffic and Motor Vehicle Safety Act of 1966 (autosafety.org), an automaker has five business days to inform the NHTSA after it discovers a problem. If an automaker refuses to comply, the NHTSA can begin legal proceedings. Therefore, product recall is outside management control and is therefore treated as an exogenous variable in this study.

Following BLP (1995) and Sudhir (2001), we treat product features as exogenous variables. The product features (e.g., size, MPG, horsepower) that we use in this study are broad attributes at an aggregate level. A product recall in the automobile industry typically involves defect(s) in one or more parts that may be indirectly related to one feature. For example, a defect in a brake pad may result in the replacement of that brake pad and not lead to the redesign of a product feature. Our extensive discussions with industry executives involved in product recalls suggest that firms typically bolster the quality of supplies and manufacturing on the recall-related parts (e.g., sourcing a higher-quality brake pad or a more careful inspection of brake pad installation). There is little evidence to show that firms make major or substantial changes to aggregate level product features/characteristics based on a single recall event. Moreover, the results of the regression models of product features on product recalls show no significant effect of product recall on product features in the data.

5.2.3. Endogeneity of Price, Advertising, and Media Coverage. Price and advertising are endogenous because firms may make adjustments to their marketing strategy when anticipating demand shocks unobserved by researchers. For example, when introducing a New Year version on a nameplate with a better design (e.g., car facelift), a firm may offer cash back incentives and increase its advertising budget on that nameplate. Such missing variables (e.g., product aesthetic appearance) may increase demand, leading to biased estimates of price and advertising.

To account for the endogeneity of price, we follow BLP (1995) and use the classic instrumental variable estimation techniques developed for the random coefficient model. Following BLP (1995), Sudhir (2001), and Balachander et al. (2009), we use functions of own and competitors' product characteristics as instruments. Specifically, to create two similarity subsets for each car, we use the following classification variables obtained from *Ward's Automotive Yearbook*, country of origin (United States, Japan, Europe, and Korea), design classification (regular, specialty, and sporty), and car segment (small, medium, large, and luxury). The two similarity subsets we create are (1) all cars having the same country of origin and belonging to the same car segment and (2) all cars having the same *Ward's* design classification and belonging to the same car segment. We then generate instruments by computing the within-firm sum and the across-firm sum of car characteristics for the two similarity subsets. For example, VW Jetta is classified as a regular car by *Ward's* and is a European car in the medium segment. Therefore, the two similarity subsets for VW Jetta are (1) all medium-size European cars and (2) all medium-size regular cars. We compute the within-firm (VW) sum and the across-firm sum of characteristics such as MPG and HPWT for both similarity subsets to create instruments. As in Sudhir (2001), these instruments are valid because a brand's oligopoly equilibrium prices are correlated with its features as well as those of the competitors. Moreover, these instruments are exogenous because a firm cannot change its car's features in the short run.

We account for the endogeneity of advertising using the control function approach, consistent with Petrin and Train (2010) and Luan and Sudhir (2010). Specifically, we consider both intercept and slope endogeneity. We assume that econometrically unobserved factors affect advertising spending, inducing the intercept endogeneity problem. Furthermore, manufacturers may have private information about how the market will respond to advertising (advertising effectiveness parameter) that leads to the slope endogeneity problem. We include two sets of instruments for advertising. The first set of instruments comprises advertising costs across media, consistent with prior research (Dube et al. 2005, Sriram et al. 2006, Luan and Sudhir 2010, Kim and Chintagunta 2012). The rationale is that a firm's advertising spending may be influenced by advertising costs.[13] Advertising cost is reasonably exogenous because it is common across brands and does not change in anticipation of demand shocks. Ad$pender reports data on firms' dollar spending on advertising as well as on their units of exposures in each of the following media; cable TV, network TV, syndication TV, spot TV, Sunday magazines, daily magazines, and national newspapers. We use the average unit cost of each medium in nonpassenger car categories (e.g., SUV, minivan, light truck) as a proxy for advertising cost in passenger car market.[14] Because the advertising costs do not vary by brand, these instruments alone may not explain the differences in advertising spending across brands. Therefore, we utilize a second set of instruments for advertising; own and competitors' product characteristics, same as those we use for correcting price endogeneity. These instruments are valid because when facing competition, the firm may change its advertising budget based on relative features of own and competitors' features. In addition, the assumption on the exogeneity of these instruments is reasonable because firms cannot easily change product features in the short run.

Media coverage can also be endogenous. This is because newsworthy recall events may attract more media attention. Consumers are likely to respond more negatively to such recalls as well. For example, recalls on a popular brand (e.g., Toyota Camry), may be more newsworthy than others (e.g., Mitsubishi 3000) and thus attract more media attention. We again adopt the control function approach to account for the endogeneity of media coverage arising from such sources. We use the media coverage on the parent brand's latest recalls in three other product categories, including minivan, SUV and light trucks, as instruments.[15] This is logical because recalls on different products (e.g., sedan, SUV) under the same parent-brand name (e.g., Toyota) may attract similar level of media attention, so our instruments are intuitively correlated with the endogenous variable. Moreover, the average time since the most recent recall in other product categories is 13.5 months. We expect limited impact on the focal category demand of media attention to such recalls occurred more than a year ago, so our instruments are plausibly exogenous. One limitation of these instruments is that because they are at the parent-brand level, the endogeneity issue still remains if some unobserved recall event-specific factors are correlated with both media attention and demand. Therefore, to appropriately identify

[13] Depending on the increase (decrease) in advertising units after a drop (increase) in unit price, advertising cost may have a positive or a negative relationship with total advertising spending.

[14] For parent-brand-level advertising, A_{it}, we use the average values of the product characteristics across all the nameplates of a parent brand. We use the same sets of instruments for both parent-brand-level advertising and nameplate-level advertising because a firm simultaneously decides how much to spend on each advertising type. Moreover, the data show significant correlation (0.32, $p < 0.01$) between the spending on these two advertising types.

[15] For parent brands with no recalls in these three product categories in the last three years, we use the average media coverage of the most recent recalls on all other parent brands in this category.

the effect of media coverage, it is important to include certain controls at the recall event level. The two other recall characteristic variables, recall severity and the expected quality of the recalled nameplate, serve as such controls. The intuition is that recalls with greater severity usually attract more media attention. Moreover, a high quality nameplate is less likely expected to recall its product, so when it does, it may attract more media attention.

6. Results

6.1. Model Comparison

To justify the importance of incorporating a product recall's direct and indirect effects on brand preference and the dynamics in consumer response to advertising and product recall, we compare our proposed model with a few nested models: (1) Model 1, a model considering constant advertising effectiveness and no product recall effects; (2) Model 2, a model based on Model 1 by incorporating constant direct effects of product recalls (both own and cross recalls) on brand preference. The first two models do not consider time-varying advertising and product recall coefficients; (3) Model 3, the full model, which also includes time-varying advertising effectiveness and recall effects. We use the model and moment selection criteria–Akaike information criteria (MMSC-AIC), a selection criterion for nested or nonnested GMM model selection (Andrews and Lu 2001) to compare the fit of these five models. Specifically, $MMSC\text{-}AIC = O\text{-}2 \cdot (k_m - k_b)$, where O is the value of the GMM objective function, k_m is the number of moments, and k_b is the number of parameters to be estimated.

We start with the first two models that consider neither time-varying advertising effectiveness nor time-varying consumer response to product recall. The values of MMSC-AIC and the objective function in Table 3 show that the fit of Model 1 is significantly worse than Model 2, underlining the importance of considering a product recall's direct effect on brand preference. Next, we compare Model 2 with the full model (Model 3), which incorporates a product recall's direct effect on advertising effectiveness and differential recall effects due to recall characteristics (i.e., time-varying advertising effectiveness and recall effects). The values of MMSC-AIC and the objective function of the full model show significant improvements. Therefore, it is important to model a product recall's impact on advertising effectiveness (indirect effect on brand preference) and time-varying and heterogeneous recall effects in the full model.

6.2. Full Model Estimation Results

We present the full model estimation results in Tables 4 and 5. We first discuss the *direct effect* of product recall on brand preference and how recall characteristics impact this effect. Recall that we model the effects of three recall characteristics (λ_{ijt}^R) with a random walk specification. Thus, the recovered recall characteristics coefficients (λ_{ijt}^R) depend on both initial values λ_{ij0}^R and the standard deviations of the error terms in the recall characteristic equation (Equation (9)) $\sigma_{\lambda 1}$.

The initial effects of three recall characteristics (λ_{ij0}^R) are all significantly negative ($p < 0.05$). Moreover, the standard deviation of the error terms $\sigma_{\lambda 1}$ is insignificant with very small value (2.21×10^{-3}, $p > 0.1$). Therefore, the recovered recall characteristics coefficients (λ_{ijt}^R) stay negative over time for all the nameplates. The negative media coverage coefficients suggest that greater publicity of product recall events enhances consumers' negative perceptions of the brand, consistent with Siomkos and Kurzbard (1994). The coefficients of recall severity are negative over time, indicating that severity type 1 recall has a greater direct impact on brand preference than severity type 2 recall. This is because although severity type 2 recall also has an injury consequence, it is conditional on the occurrence of an auto crash that may not be caused by product defect (e.g., reckless driving). Therefore, customers may not respond as

Table 3 **Structural Model Comparison**

Variable	Model 1 Estimate (S.E.)	Model 2 Estimate (S.E.)	Model 3 Full model
Nameplate-level ad effectiveness: q^A	1.29 (0.06)***	1.31 (0.10)***	See Table 4
Parent-brand-level ad effectiveness: q^A	0.17 (0.01)***	0.19 (0.07)***	
Brand preference carryover rate: δ^g	0.86 (0.13)***	0.87 (0.10)***	
Recall direct effect (q^R): λ_0		−0.47 (0.08)***	
Recall spillover effect (q^s): λ_2		−0.19 (0.01)***	
Objective function	181.91	161.91	132.74
MMSC-AIC	293.91	277.91	274.74

Notes. S.E., standard error. The estimates of car characteristic and price parameters are not shown to save space. $\ln(PR_{ijt}+1)$ and $\ln(A_{ijt}+1)$ are rescaled by multiplying them by 0.1 and 0.01, respectively.
***Significant at 0.01.

Table 4 Results of Full Structural Model: Mean Utility Parameters

Product recall and advertising variables	Estimate (S.E.)
Direct effects of recall q_{ijt}^R	
Constant term: q_0^R	−0.14 (0.08)**
Initial media coverage effects: $\lambda_{0\_media}^R$	−0.03 (0.02)**
Initial severity effects: $\lambda_{0\_severity}^R$	−0.37 (0.11)***
Initial reliab effects: $\lambda_{0\_reliab}^R$	−0.20 (0.10)**
Carryover rate of strong brand: δ_1^R	0.10 (0.05)**
Carryover rate of weak brand: δ_2^R	0.09 (0.03)***
Ad effectiveness q_{ijt}^A	
Parent brand level	
Constant term: $q_{0\_parent}^A$	0.13 (0.08)*
Initial indirect effect of recall: $\lambda_{0\_parent}^A$	−0.13 (0.06)**
Nameplate level	
Constant term: $q_{0\_nameplate}^A$	1.25 (0.17)***
Initial indirect effect of recall: $\lambda_{0\_nameplate}^A$	−0.49 (0.05)***
Carryover rate of strong brand: δ_1^A	0.22 (0.06)***
Carryover rate of weak brand: δ_2^A	0.20 (0.09)**
Spillover effect of recall on strong brand: q_1^s	−0.09 (0.02)***
Spillover effect of recall on weak brand: q_2^s	−0.08 (0.04)**
Carryover rate of preference for strong brand: δ_1^g	0.89 (0.20)***
Carryover rate of preference for weak brand: δ_2^g	0.83 (0.29)**
Observation equation error's S.D.: σ_ξ	0.03 (0.00)***
Brand preference equation error's S.D.: σ_v	3.11×10^{-4} (6.16×10^{-5})***
Ad effectiveness equation error's S.D.: σ_A	0.04 (0.00)***
Recall parameter equation error's S.D.: σ_R	2.21×10^{-3} (1.50×10^{-3})
Recall characteristic equation error's S.D.: $\sigma_{\lambda 1}$	1.38×10^{-3} (8.59×10^{-3})
Indirect effect equation error's S.D.: $\sigma_{\lambda 2}$	2.88×10^{-3} (1.43×10^{-3})**
Intercept endogeneity: Parent-brand-level ad (A_{it-1}^p)	0.04 (0.00)***
Intercept endogeneity: Nameplate-level ad (A_{ijt-1}^n)	−0.03 (0.01)***
Slope endogeneity: A_{it-1}^p on the effectiveness of A_{ijt-1}^n	0.09 (0.02)***
Slope endogeneity: A_{it-1}^p on the effectiveness of A_{it-1}^p	−0.30 (0.03)***
Slope endogeneity: A_{ijt-1}^n on the effectiveness of A_{ijt-1}^n	−0.25 (0.31)
Slope endogeneity: A_{ijt-1}^n on the effectiveness of A_{it-1}^p	0.01 (0.01)
Endogeneity: Media coverage	0.02 (0.01)**
EUR	1.92 (0.11)***
US	0.24 (0.05)***
JAP	0.41 (0.16)***
Q1	−0.05 (0.30)
Q2	0.05 (0.03)*
Q3	0.01 (0.00)***

Notes. S.E., standard error; S.D., standard deviation. *Reliab*, *Media*, *Severity*, $\ln(PR_{ijt}+1)$, and $\ln(A_{ijt}+1)$ were rescaled by multiplying them by 0.1, 0.1, 0.1, 0.1, and 0.01, respectively. The initial brand preference parameters g_{i0} are not shown to save space. They range from −2.70 (Mini Cooper) to 1.01 (Oldsmobile). South Korea as the country of origin and Q4 (quarter 4) form the base case.

*Significant at 0.10; **significant at 0.05; ***significant at 0.01.

negatively for severity type 2 recall as they do for severity type 1.

The coefficients of expected quality of the recalled brand (i.e., reliability) are negative over time, indicating that consumer brand preference decreases with prior product quality expectation. This finding supports the theory of expectancy-violation effects (Burgoon and LePoire 1993). That is, consumers respond more negatively to the recall of a brand with high quality because such a negative event is inconsistent with their prior expectations. Furthermore, because the coefficient of the constant term (q_0^R) in the recall direct effect Equation (Equation (8b)) is significantly negative (−0.14, $p < 0.05$), together with negative recovered recall characteristics coefficients (λ_{ijt}^R), we conclude that product recall has a negative direct effect on consumer brand preference, as expected. The carryover rate of consumer response to product recall δ^R is significant ($p < 0.05$) for both strong and weak brands. This result implies that the effects of recall characteristics (M_{ijt}) occur over the long term. Therefore, consumer response to recalls in successive periods differs from response to a single isolated recall. Moreover, δ^R of strong brands (0.10, $p < 0.05$) is greater than that of weak brands (0.09, $p < 0.01$), indicating that the negative impact of recall characteristics lasts longer for strong brands. This intuitive because strong brands may be hurt more during a product-harm crisis.

We now discuss a product recall's effects on advertising effectiveness (i.e., *indirect effect* of product recall on brand preference) and all the other parameters in the advertising effectiveness equation (Equation (8a)). The constant term of nameplate-level advertising effectiveness ($q^A_{0\_\text{parent}} = 1.25$, $p < 0.01$) is greater than that of the parent-brand-level advertising effectiveness ($q^A_{0\_\text{nameplate}} = 0.13$, $p < 0.01$), indicating that nameplate-level advertising is more effective than parent-brand-level advertising when there is no product recall. Again, the recovered coefficients of a product recall's effect on advertising effectiveness (λ^A_{ijt}) depend on both the initial value λ^A_{ij0} and the standard deviation of the error terms in the recall characteristic Equation (Equation (9)) $\sigma_{\lambda 2}$. The initial effects of product recall on nameplate-level advertising effectiveness, $\lambda^A_{0\_\text{parent}}$, and parent-brand-level advertising effectiveness, $\lambda^A_{0\_\text{nameplate}}$, are -0.49 ($p < 0.01$) and -0.13 ($p < 0.05$), respectively. With small standard deviation of the error terms (2.21×10^{-3}, $p > 0.1$), the recovered coefficients of a product recall's effect on nameplate-level advertising are in general greater (more negative) than those of a product recall's effect on parent-brand-level advertising effectiveness. These findings indicate that the effectiveness of advertising featuring the recalled nameplate declines by a greater amount during a crisis. The carryover rates of advertising effectiveness δ^A are significant for both strong and weak brands, suggesting that a product recall's effect on advertising effectiveness occurs over the long term. Moreover, such carryover rates are greater for strong brands than weak brands (0.22 versus 0.20), indicating that it takes a longer period for advertising for a strong brand to recover to its original effectiveness.

The spillover effect of product recall is significantly negative for both brand types ($p < 0.05$), implying that the negative effect of product recall can transfer to all other nameplates of the same parent brand, consistent with our expectation. The monthly carryover rate of preference for strong and weak brands are 0.89 ($p < 0.01$) and 0.83 ($p < 0.01$), respectively, consistent with previous studies (e.g., Naik et al. 1998). Furthermore, the estimates for the endogeneity correction parameters confirm our conjecture that both manufacturer spending on advertising and media coverage are endogenous. The coefficients for the country of origin show that the average consumer prefers European cars most, followed by Japanese and American cars. The coefficients of Q1, Q2, and Q3 show that seasonality has the largest effect on demand in the second quarter, followed by the third and fourth quarters.

Table 5 **Results of Full Structural Model Continued: Heterogeneity Parameters**

Control variables	Mean (S.E.)	S.D. (S.E.)
$\text{Ln}(Y_{ht} - P_{jt})$	3.82 (0.24)***	
HPWT	0.93 (0.05)***	0.04 (0.01)***
Size	0.15 (0.05)***	0.11 (0.06)**
MP$	0.09 (0.05)**	0.01 (0.01)
Reliab	0.22 (0.02)***	0.34 (0.30)
2DR	−1.31 (0.01)***	0.14 (0.09)*
LUX	−3.39 (2.52)	0.32 (0.02)***
Δg_{hijt}		1.09 (0.04)***

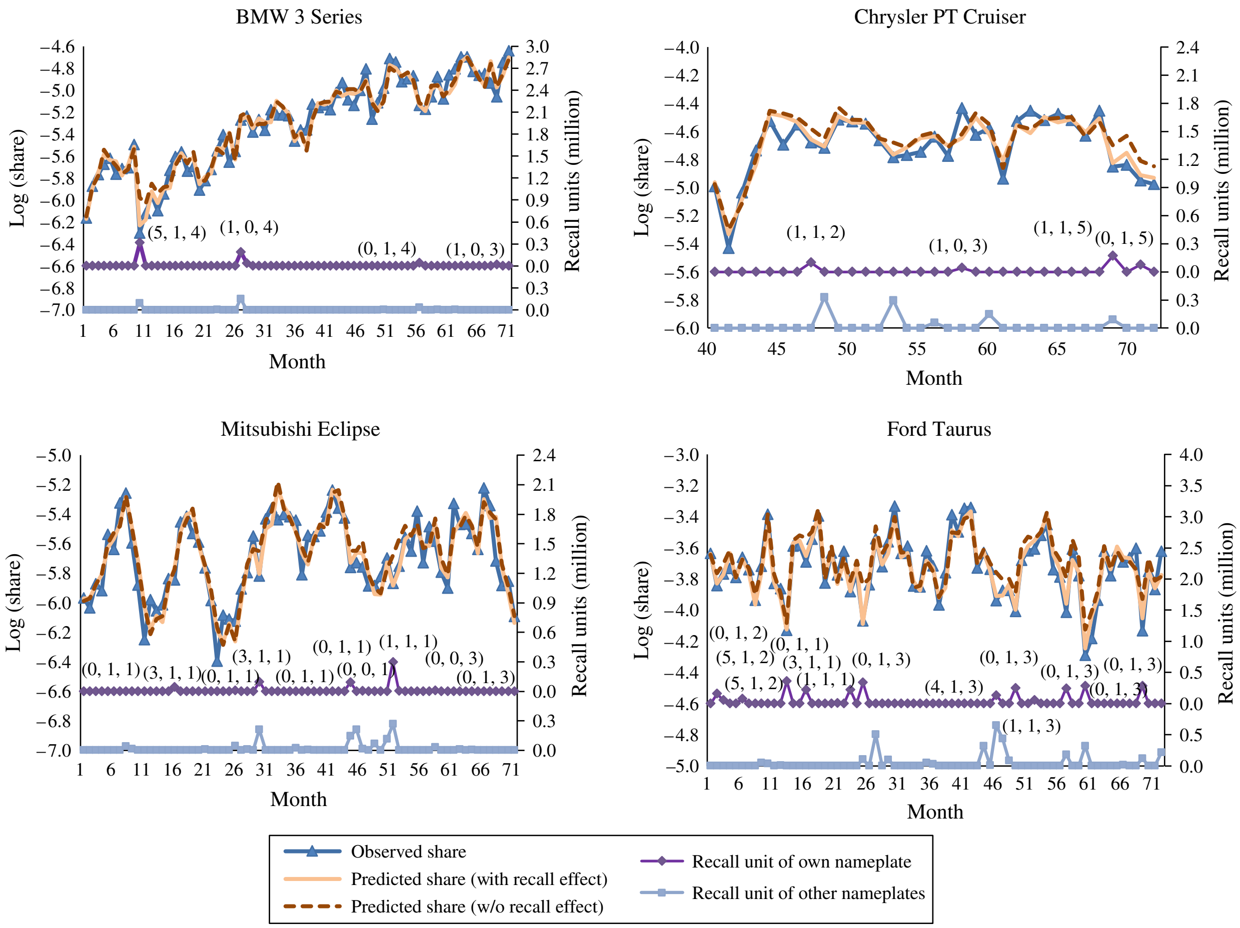
Notes. S.E., standard error; S.D., standard deviation. *HPWT*, *MP$*, and *SIZE* were rescaled by multiplying them by 100, 0.1, and 0.0001, respectively.
*Significant at 0.10; **significant at 0.05; ***significant at 0.01.

Finally, we discuss the results on price and product characteristics (Table 5). The income and price coefficient (of $\ln[Y_{ht} - p_{ijt}]$) is positive and significant (3.82, $p < 0.01$), as expected. Consistent with our expectations, the coefficients of *HPWT*, *SIZE*, *MP$*, and *Reliab* are positive and significant ($p < 0.05$) and the coefficients of the dummy variable *2DR* is negative and significant ($p < 0.01$). These findings indicate a high preference for cars with high horse power, large size, high fuel efficiency, and high reliability and a low preference for two door cars. All the heterogeneity parameters except those of *MP$* and *Reliab* are statistically significant ($p < 0.10$), suggesting considerable differences across consumers.

6.3. Decomposition of Product Recall Effect

To demonstrate a product recall's impact on the market shares and sales of the car nameplates in our data, we first select four car nameplates, BMW 3 Series, Chrysler PT Cruiser, Mitsubishi Eclipse, and Ford Taurus, which represent the luxury car, new car, specialty car, and regular car categories, respectively. We then plot the log of observed market share and the log of estimated (predicted) market share with and without product recall effects over the estimation (first 60 months) and validation (last 12 months) periods in Figure 2. The model with product recall effects predicts market shares better than the one without product recall effects for all four car nameplates in both the estimation and validation samples. Importantly, firms can be overoptimistic about their forecasted market shares if they do not consider product recall effects (Figure 2). This finding underscores the importance of modeling product recall effects. Moreover, the impact of product recall (e.g., market share loss), indicated by the difference between the predicted market share with and without product recall effects, greatly varies across recall events. The loss in market share increases with the units recalled, as expected. Furthermore, the negative impact of recalls with similar magnitude differs across recall characteristics. For

Figure 2 (Color online) Observed and Estimated/Predicted Market Shares: Selected Nameplates



Note. Numbers in the parentheses are (media coverage, severity, reliability).

example, although Mitsubishi Eclipse recalled similar amount of cars (93,000) in Weeks 30 and 45, the dip in its market share is greater in Week 30 because it attracted a greater media attention.

Table 6 reports the predicted losses in market shares and dollar sales due to product recall effects for these four car nameplates. Because the negative effect of product recall can carry over from previous periods, we report these losses in both the short term (at the time of recall) and the long term (periods after recall). In addition, we decompose the long-term sales loss into four components: loss due to the direct effect of product recall on brand preference, loss due to the indirect effect of product recall on brand preference through decreased nameplate-level advertising effectiveness, loss due to the indirect effect of product recall on brand preference through decreased parent-brand-level advertising effectiveness, and loss due to product recalls of other name plates under the same brand (spillover effect).

Table 6 shows that all four car nameplates suffer substantial losses in market share and sales in the short term. These losses become even more damaging in the long term because of the carryover effect. We now focus on the long-term loss and compare the differences among these four car nameplates. Figure 2 shows that BMW 3 Series has the least number of product recalls (both own nameplate recall and recalls of other nameplates under the same parent-brand name) in the first 60 months. Therefore, BMW 3 Series suffers the least percentage loss in market share among the four car models in the estimation period (Table 6). However, its loss in dollar sales is not the smallest among these four cars because of its high unit price. Chrysler PT Cruiser was a newly introduced nameplate with a small number of recalls of moderate severity during the estimation period. However a few recalls on the other nameplates of Chrysler brand have substantial impact during the estimation period. Because of this spillover effect, Chrysler PT Cruiser suffers a greater loss in market share than BMW 3 Series. Mitsubishi Eclipse and Ford Taurus are among the most frequently recalled nameplates in the sample. However, the recalls on Ford

Table 6 Decomposition of Losses During a Product-Harm Crisis

	BMW 3 Series	Chrysler PT Cruiser	Mitsubishi Eclipse	Ford Taurus
	Estimation sample (first 60 months)			
Observed				
Market share (%)	0.48	0.31	0.35	2.50
Sales (million $)	10,897.57	3,352.96	4,900.73	36,507.97
Short-term loss				
% loss in market share	−0.18	−0.37	−0.42	−1.92
Total loss in sales (million $)	−19.67	−12.41	−20.79	−702.38
Long-term loss				
% loss in market share	−0.66	−1.26	−1.38	−6.24
Total loss in sales (million $)	−71.44	−42.21	−67.68	−2,279.70
Decomposition of long-term loss in sales (% of total loss)				
Direct effect	−49.75	−14.59	−24.78	−1,238.11
	(−69.64%)	(−34.56%)	(−36.61%)	(−54.31%)
Indirect effect: Nameplate-level ad effectiveness	−11.13	−3.77	−14.11	−473.70
	(−15.58%)	(−8.93%)	(−20.89%)	(−20.78%)
Indirect effect: Parent-brand-level ad effectiveness	−3.56	−1.32	−4.10	−151.59
	(−0.99%)	(−3.13%)	(−6.06%)	(−6.65%)
Spillover effects	−7.00	−22.530	−24.66	−416.31
	(−9.79%)	(−53.38%)	(−36.44%)	(−18.26%)
	Validation sample (last 12 months)			
Observed				
Market share (%)	0.80	0.96	0.37	2.23
Sales (million $)	3,696.01	2,239.25	1,041.31	6,483.73
Short-term loss				
% loss in market share	−0.04	−1.87	−0.02	−1.47
Total loss in sales (million $)	−1.42	−41.92	−0.19	−95.27
Long-term loss				
% loss in market share	−0.15	−6.39	−0.05	−5.54
Total loss in sales (million $)	−5.57	−143.07	−0.54	−359.40
Decomposition of long-term loss in sales (% of total loss)				
Direct effect	−3.01	−92.33	−0.01	−214.49
	(−54.10%)	(−64.53%)	(−1.01%)	(−59.68%)
Indirect effect: Nameplate-level ad effectiveness	−1.47	−25.58	0.00	−45.43
	(−26.33%)	(−17.8%)	(−0.36%)	(−12.64%)
Indirect effect: Parent-brand-level ad effectiveness	−0.51	−7.16	0.00	−14.53
	(−9.22)	(−5.01%)	(−0.11%)	(−4.04%)
Spillover effects	−0.58	−18.00	−0.53	−84.96
	(−10.35%)	(−12.58%)	(−98.52%)	(−23.64%)

Note. The percentages in parentheses add up to 100 within the same decomposition in the same column.

Taurus involve a much higher number of units (Figure 2), so Ford Taurus suffers significantly greater losses than Mitsubishi Eclipse in market share (6.24% versus 1.38%) and in sales ($2,279.70 million versus $67.68 million). During the validation period, the sales of Ford Taurus are hurt the most because of a relatively high number of recalls of own nameplate as well as those of other Ford nameplates.

We now discuss the decomposition of the losses. In the first 60 months, the direct effect of product recall on brand preference contributes the most to the losses for all four car models except for Chrysler PT Cruiser. The recalled units of Chrysler PT Cruiser nameplate are significantly lower than the recalled units of other Chrysler nameplates, so PT Cruiser's losses due to spillover effects is greater than those due to the direct effect of its own recalls. The decreased effectiveness of nameplate-level advertising during product recall accounts for about 9%–21% of the total loss for these four car models. Since parent-brand-level advertising is hurt less than nameplate-level advertising during product recall, the loss due to the decreased effectiveness of parent-brand-level advertising is smaller and ranges from about one percent to seven percent. Therefore, firms should allocate less of their budget to promote the recalled nameplates and spend more on parent-brand-level advertising. The spillover effect contributes about 10%–53% to the sales loss for these four car nameplates, depending on the magnitudes and number of recalls on other car nameplates of the same brand. In the validation period, we observe similar decomposition ratios except for Mitsubishi Eclipse

Table 7 Policy Simulation Analysis: Effect of Reallocation of Advertising Under Different Scenarios

Policy-change scenario	Market share/sales	Chrysler	Ford	Honda	Chevrolet	Average brand
Observed	Market share (%)	2.37	6.32	5.36	5.49	1.78
	Sales (million $)	6,343.36	16,475.94	13,116.96	14,086.35	5,215.84
Scenario 1: Reallocate one-third of recalled-nameplate-level ad to parent-brand-level ad	Gain in market share (%)	0.01 (0.43%)	0.04 (0.62%)	0.45 (0.83%)	0.03 (0.48%)	0.01 (0.38%)
	Gain in sales (million $) (%)	23.66 (0.37%)	86.01 (0.52%)	103.72 (0.79%)	62.09 (0.44%)	15.62 (0.35%)
Scenario 2: Reallocate two-thirds of recalled-nameplate-level ad to parent-brand-level ad	Gain in market share (%)	0.02 (0.85%)	0.07 (1.12%)	0.08 (1.46%)	0.05 (0.86%)	0.01 (0.59%)
	Gain in sales (million $) (%)	56.27 (0.89%)	183.69 (1.11%)	206.70 (1.58%)	113.00 (0.80%)	26.99 (0.60%)
Scenario 3: Reallocate all of recalled-nameplate-level ad to parent-brand-level ad	Gain in market share (%)	0.03 (1.28%)	0.07 (1.15%)	0.11 (2.10%)	0.07 (1.19%)	0.02 (1.12%)
	Gain in sales (million $) (%)	82.30 (1.30%)	200.94 (1.22%)	264.23 (2.01%)	181.46 (1.29%)	45.32 (1.01%)

Note. The percentages in parentheses are changes from observed market share or sales.

that has only two minor recalls. The majority (99%) of the loss in its sales is due to the recalls of other Mitsubishi nameplates (spillover effect).

6.4. Policy-Change Analysis

To better understand the implications of decreased advertising effectiveness during product-harm crises and to assist firms to better allocate their advertising budgets across different types of advertising and reduce the loss due to the negative impact of product recall, we conduct a policy simulation using the estimated parameters of our model as inputs.[16] This simulation differs from supply side analysis in the classic random coefficient model (BLP 1995, Sudhir 2001) where optimal firm decision is assumed. We follow Dube et al. (2005) and Sriram et al. (2006) and do not impose any "optimality" on the firms' decision when estimating the demand model. We then let the data tell us if there is room for the firms to improve their advertising allocation rules using policy simulation. Because the effectiveness of recalled-nameplate advertising is hurt more than that of parent-brand-level advertising, we allow the firms to spend less on recalled-nameplate advertising and more on parent-brand-level advertising. We expect the reallocation of advertising spending not only to reduce the loss for the recalled nameplates but also to benefit all other nameplates of the same parent brand because of increased parent-brand-level advertising spending. We consider the following three advertising reallocation strategies in the validation period. In Scenario 1 (2), each parent brand reallocates one-third (two-thirds) of all its advertising spending from recalled nameplates to the parent brand. In Scenario 3, each parent brand allocates all its advertising spending from recalled nameplates to the parent brand.

Table 7 reports the average gains in market share and sales of parent brands under each scenario. It also shows the gains for four select parent brands, Chrysler, Ford, Honda, and Chevrolet, that have the greatest number of units recalled in the validation period. The results show that the greater the proportion of recalled-nameplate advertising to parent-brand-level advertising, the greater are the gains in market share and sales. The average parent brand gains $45.32 million in sales (1.01% increase) by reallocating all the advertising spending on recalled nameplate to its parent brand. Honda has the greatest number of cars recalled in the validation period, so it benefits the most from the advertising reallocation. If all of recalled-nameplate advertising spending is allocated to parent-brand-level advertising, the sales of the Honda brand will increase by 2.01% ($264.23 million) during the validation period. This increase is followed by that of the Ford brand (1.22% and $200.91 million). Chevrolet and Chrysler will also enjoy sales increases of 1.29% ($181.46 million) and 1.30% ($82.30 million), respectively. The gains from reallocation are substantial, highlighting the managerial usefulness of our model.

7. Conclusion and Limitations

We have developed a model that incorporates the dynamic effects of product recalls on brand preference, advertising effectiveness and market share. We began with a demand model of consumer brand

[16] We assume that other brands do not change their advertising expenditures. We realize that this assumption does not overcome the Lucas critique, so we do not suggest that these policies are optimal. Rather, we simply use this exercise to illustrate the usefulness of our results.

choice as a function of brand preference, price and car characteristics. We then used a state space model to analyze a product recall's long-term direct and indirect effects on unobserved brand preference. The model also allowed us to study how these negative effects of product recall vary by recall characteristics, such as recall severity, media coverage of the recall, and expected quality of the recalled brand. We integrated the state space model with a random coefficient demand model and estimated it.

Our results help firms better understand a product recall's effects, make better decisions on advertising spending, and rebuild brand preference after product recalls. Our results reveal that product recall has a negative direct effect on brand preference. This effect increases with recall severity, media coverage surrounding the event, and consumers' expected quality of the recalled brand. In addition, product recall can indirectly impact brand preference by influencing the effectiveness of advertising. Specifically, advertising featuring the recalled nameplate suffers more than advertising featuring the brand. Thus, firms should allocate less of their budgets to the recalled car nameplate. Furthermore, a product recall on one car nameplate can negatively impact consumer preference for all other car nameplates under the same parent-brand name. Finally, the policy simulation exercise suggests that firms can substantially benefit from advertising reallocation during a product-harm crisis.

Our research has certain limitations that future research could address. First, although our model allows us to investigate how product recalls affect own nameplate (own effects) and all other nameplates of the same parent brand (spillover effects) and enables us to capture how product recall operates at both nameplate (e.g., Toyota Camry) and parent-brand (e.g., Toyota) levels, future research could explicitly model a product recall's effects on consumer preference at both levels.

Second, we allowed the carryover rate to be brand-type specific rather than nameplate specific. To test whether the carryover rate indeed greatly varies across brands, we estimated a model with parent-brand-level carryover rate. For parsimony, we did not consider time-varying advertising and recall effects. All the carryover rates except that for Daewoo (0.76) fall in the (0.82–0.88) range. Thus, we believe the impact of not including nameplate-level carryover rate is minimum in our study. With additional data, future research could investigate nameplate-specific carryover rate.

Third, our choice model could also be extended to include forward-looking behavior, extending Schiraldi (2011) and Dube et al. (2012). However, it would be challenging to formulate consumer expectations of future recall events because of the random nature of occurrence of product recalls.

Fourth, because of data limitation, we did not consider social media's impact on consumer response to product recall. Our data period is from 1997 to 2002 before social media became popular. Future research can attempt this extension with more recent data.

Fifth, we did not account for a product recall's impact on consumer response to price or promotion. To test if product recall may influence consumer price sensitivity in our data, we add an interaction term between product recall and price in Equation (1). The estimation results show that these interaction terms are insignificant ($p > 0.10$), suggesting that there is no effect of product recall on price sensitivity in the data. Therefore, we do not consider such an effect of product recall. Because the price variable is inflation-adjusted MSPR, which have little month-to-month variation in our study, future research may reexamine the effect of product recall on price sensitivity with transactional price. Similarly, the impact of product recall on consumer response to promotion can be studied with suitable data in the future.

Sixth, we include two types of advertising, brand level and parent-brand-level advertising. During a product-harm crisis, firms may switch from brand-building advertising to defensive advertising or apology advertising to alleviate the damage. Because we do not observe the content of the advertising, such advertising spending change within the same advertising type are not modeled and may be tested in future research.

Seventh, our instruments for price, advertising and media coverage have some potential caveats, induced primarily by potential correlation with demand shocks. For example, during economic downturns, demand for cars may drop along with the prices for most goods and services, including advertising rates. As another example, a two-door car may have an attractive design (e.g., Ford Mustang), an unobserved product characteristic, weakening the exogeneity of product characteristic. Moreover, product attributes may not change in the short term and thus may not be able to control for endogeneity arising from short-term price changes triggered by unobserved short-term demand shocks. Because of limited access to appropriate data, resolving this issue beyond any reasonable doubt is difficult, so we leave this issue for future research.

Finally, our dynamic model estimation involves two variances, one from the contraction mapping and the other from the KF. These two variances should be equal at each step of the optimization process, but the extant method does not impose this constraint because it uses a linear KF version to solve an inherently nonlinear problem. This method could be improved by a future methodological breakthrough.

Acknowledgments

The authors thank S. Sriram, Subramanian Balachander, participants at the Marketing Science Conference 2012 and UT Dallas FORMS Conference 2012 for valuable comments. They thank Mays Business School's support for obtaining data used in this study.

References

Aaker J, Fournier S, Brasel SA (2004) When good brands do bad. *J. Consumer Res.* 31(1):1–16.

Ahluwalia R, Burnkrant RE, Unnava HR (2000) Consumer response to negative publicity: The moderating role of commitment. *J. Marketing Res.* 37(2):203–214.

Andrews DWK, Lu B (2001) Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *J. Econometrics* 101(1):123–164.

Ataman MB, Van Heerde HJ, Mela CF (2010) The long-term effect of marketing strategy on brand sales. *J. Marketing Res.* 47(5): 866–882.

Balachander S, Liu Y, Stock A (2009) An empirical analysis of scarcity strategies in the automobile industry. *Management Sci.* 55(10):1623–1637.

Bass FM, Bruce N, Majumdar S, Murthi BPS (2007) Wearout effects of different advertising themes: A dynamic Bayesian model of the advertising-sales relationship. *Marketing Sci.* 26(2): 179–195.

BBC News (2010) Toyota car recall may cost $2bn. (February 2), http://news.bbc.co.uk/2/hi/business/8493414.stm.

Berger J, Sorensen AT, Rasmussen SJ (2010) Positive effects of negative publicity: When negative reviews increase sales. *Marketing Sci.* 29(5):815–827.

Berry S, Levinsohn J, Pakes A (1995) Automobile prices in market equilibrium. *Econometrica* 63(4):841–891.

Burgoon JK, LePoire BA (1993) Effects of communication expectancies, actual communication, and expectancy disconfirmation on evaluations of communicators and their communication behavior. *Human Comm. Res.* 20(1):67–96.

Chen Y, Ganesan S, Liu Y (2009) Does a firm's product-recall strategy affect its financial value? An examination of strategic alternatives during product-harm crises. *J. Marketing* 73(6): 214–226.

Cleeren K, van Heerde HJ, Dekimpe M (2013) Rising from the ashes: How brands and categories can overcome product-harm crises. *J. Marketing* 77(2):58–77.

Crafton SM, Hoffer GE, Reilly RJ (1981) Testing the impact of recalls on the demand for automobiles. *Econom. Inquiry* 19(4):694–703.

Davidson W III, Worrell D (1992) The effect of product recall announcements on shareholder wealth. *Strat. Management J.* 13(6):467–473.

Dawar N, Pillutla MM (2000) Impact of product-harm crises on brand equity: The moderating role of consumer expectations. *J. Marketing Res.* 37(2):215–226.

Devaraj S, Matta KF, Conlon E (2001) Product and service quality: The antecedents of customer loyalty in the automotive industry. *Production Oper. Management* 10(4):424–439.

Dube J-P, Fox JT, Su C-L (2012) Improving the numerical performance of BLP static and dynamic discrete choice random coefficients demand estimation. *Econometrica* 80(5):2231–2267.

Dube J-P, Hitsch G, Manchanda P (2005) An empirical model of advertising dynamics. *Quant. Marketing Econom.* 3(2):117–144.

Fiske ST, Taylor SE (1991) *Social Cognition* (McGraw-Hill, New York).

Hannah DB, Sternthal B (1984) Detecting and explaining the sleeper effect. *J. Consumer Res.* 11(2):632–642.

Hoffer GE, Pruitt SW, Reilly RJ (1988) The impact of product recalls on the wealth of sellers: A reexamination. *J. Political Econom.* 96(3):663–670.

Hoffman AJ, Ocasio W (2001) Not all events are attended equally: Toward a middle-range theory of industry attention to external events. *Organ. Sci.* 12(4):414–434.

Harvey AC (1991) *Forecasting, Structural Time Series Models and the Kalman Filter* (Cambridge University Press, Cambridge UK).

Jarrell G, Peltzman S (1985) The impact of product recalls on the wealth of sellers. *J. Political Econom.* 93(3):512–536.

Jedidi K, Mela CF, Gupta S (1999) Managing advertising and promotion for long-run profitability. *Marketing Sci.* 18(1):1–22.

Jensen C (2011) 2010 a record year for "voluntary" recalls. *The New York Times* (January 20), http://wheels.blogs.nytimes.com/2011/01/20/2010-a-record-year-for-voluntary-recalls/?_r=0.

Jolly DW, Mowen JC (1984) Product recall communications: The effects of source, media, and social responsibility information. Hirschman E, Holbrook M, eds. *Advances in Consumer Research* (Association for Consumer Research, Provo, UT), 471–475.

Kalaignanam K, Kushwaha T, Eilert M (2013) The impact of product recalls on future product reliability and future accidents: Evidence from the automobile industry. *J. Marketing* 77(2):41–57.

Kim M, Chintagunta PK (2012) Investigating brand preferences across social groups and consumption contexts. *Quant. Marketing Econom.* 10(3):305–333.

Kolsarici C, Vakratsas D (2010) Category- versus brand-level advertising messages in a highly regulated environment. *J. Marketing Res.* 47(6):1078–1089.

Lei J, Dawar N, Gürhan-Canli Z (2012) Base-rate information in consumer attributions of product-harm crises. *J. Marketing Res.* 49(3):336–348.

Levin DZ (2000) Organizational learning and the transfer of knowledge: An investigation of quality improvement. *Organ. Sci.* 11(6):630–647.

Laufer D, Coombs WT (2006) How should a company respond to a product harm crisis? The role of corporate reputation and consumer-based cues. *Bus. Horizons* 49(5):379–385.

Luan JY, Sudhir K (2010) Forecasting marketing-mix responsiveness for new products. *J. Marketing Res.* 47(3):444–457.

Marco CA, Suls J (1993) Daily stress and the trajectory of mood: Spillover, response assimilation, contrast, and chronic negative affectivity. *J. Personality Soc. Psych.* 64(6):1053–1063.

Naik PA, Mantrala MK, Sawyer AG (1998) Planning media schedules in the presence of dynamic advertising quality. *Marketing Sci.* 17(3):214–235.

Naik PA, Prasad A, Sethi S (2008) Building brand awareness in dynamic oligopoly markets. *Management Sci.* 54(1):129–138.

Nevo A (2001) Measuring market power in the ready-to-eat cereal industry. *Econometrica* 69(2):307–342.

Oliver RL, Winer RS (1987) A framework for the formation and structure of consumer expectations: Review and propositions. *J. Econom. Psy.* 8(4):469–99.

Pancras J, Sriram S, Kumar V (2012) Empirical investigation of retail expansion and cannibalization in a dynamic environment. *Management Sci.* 58(11):2001–2018.

Petrin A, Train K (2010) A control function approach to endogeneity in consumer choice models. *J. Marketing Res.* 47(1):3–13.

Podolny JM, Hsu G (2003) Quality, exchange, and Knightian uncertainty. *Res. Sociol. Organ.* 20:77–103.

Reilly RJ, Hoffer GE (1983) Will retarding the information flow on automobile recalls affect consumer demand? *Econom. Inquiry* 21(3):444–447.

Rhee M, Haunschild PR (2006) The liability of good reputation: A study of product recalls in the U.S. automobile industry. *Organ. Sci.* 17(1):101–117.

Robbennolt JK (2000) Outcome severity and judgments of responsibility: A meta-analytic review. *J. Appl. Psych.* 30(12):2575–2609.

Rubel O, Naik PA, Srinivasan S (2011) Optimal advertising when envisioning a product-harm crisis. *Marketing Sci.* 30(6): 1048–1065.

Schiraldi P (2011) Automobile replacement: A structural approach. *RAND. J. Econom.* 42(2):266–291.

Siomkos GJ (1999) On achieving exoneration after a product safety industrial crisis. *J. Bus. Indust. Marketing* 14(1):17–29.

Siomkos GJ, Kurzbard G (1994) The hidden crisis in product-harm crisis management. *Eur. J. Marketing* 28(2):30–41.

Smith NC, Thomas RJ, Quelch JA (1996) A strategic approach to managing product recalls. *Harvard Bus. Rev.* 74(5):102–112.

Sriram S, Chintagunta PK, Neelamegham R (2006) Effects of brand preference, product attributes, and marketing mix variables in technology product markets. *Management Sci.* 25(5): 440–456.

Sriram S, Balachander S, Kalwani M (2007) Monitoring the dynamics of brand equity using store-level data. *J. Marketing* 71(2): 61–78.

Sudhir K (2001) Competitive pricing behavior in the auto market. *Marketing Sci*. 20(1):42–60.

Suls J, Martin R (2005) The daily life of the garden-variety neurotic: Reactivity, stressor exposure, mood spillover, and maladaptive coping. *J. Personality* 73(6):1485–1510.

Szczesny JR (2010) Another safety issue: Can Toyota ever bounce back? *Time* (August 25), http://content.time.com/time/business/article/0,8599,2012701,00.html.

Thirumalai S, Sinha K (2011) Product recalls in the medical device industry: An empirical exploration of the sources and financial consequences. *Management Sci.* 57(2):376–392.

Tirunillai S, Tellis GJ (2012) Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Sci*. 31(2):198–215.

Van Heerde HJ, Helsen K, Dekimpe MG (2007) The impact of a product-harm crisis on marketing effectiveness. *Marketing Sci.* 26(2):230–245.

Van Heerde HJ, Mela C, Manchanda P (2004) The dynamic effect of innovation on market structure. *J. Marketing Res.* 48(2): 166–183.

Van Heerde HJ, Gijsenberg MJ, Dekimpe MG, Steenkamp JBE (2013) Price and advertising effectiveness over the business cycle. *J. Marketing Res*. 50(2):177–193.

Weinberger MG, Romeo JB (1989) The impact of negative product news. *Bus. Horizons* 2(1):44–50.

West M, Harrison PJ (1997) *Bayesian Forecasting and Dynamic Models* (Springer, New York).

Wynne A, Hoffer G (1976) Auto recalls: do they affect market share? *Appl. Econom.* 8(3):157–163.

Zautra AJ, Affleck GG, Tennen H, Reich JW, Davis MC (2005) Dynamic approaches to emotions and stress in everyday life. *J. Personality* 73(6):1511–1538.

Zhao Y, Zhao Y, Helsen K (2011) Consumer learning in a turbulent market environment: Modeling consumer choice dynamics in the wake of a product-harm crisis. *J. Marketing Res.* 48(2): 255–267.