Kartik Kalaignanam, Tarun Kushwaha, & Meike Eilert

The Impact of Product Recalls on Future Product Reliability and Future Accidents: Evidence from the Automobile Industry

Although the goal of a product recall program is to enhance safety, little is known about whether firms learn from product recalls. This study tests the direct effect of product recalls on future accidents and future recall frequency and their indirect effect through future product reliability in the automobile industry. The authors test the hypotheses on 459 make/year observations involving 27 automobile makers between 1995 and 2011. The findings suggest that increases in recall magnitude lead to decreases in future number of injuries and recalls. This effect, in turn, is partially mediated by future changes in product reliability. The results also suggest that the positive relationship between recall magnitude and future product reliability is (1) stronger for firms with higher shared product assets and (2) weaker for brands of higher prior quality. The findings are robust across alternate measures and alternate model specifications and offer valuable insights for managerial practice and public policy.

Keywords: product recalls, product reliability, accidents, shared product assets, prior brand quality

The increase in the number of product recalls in the past few decades is well documented in business reports. According to the Consumer Product Safety Commission (CPSC), in 2010, there was an exponential increase in the number of consumer products that were deemed hazardous and consequently withdrawn from the marketplace (CPSC 2010). In May 2007, the CPSC, the National Highway Traffic Safety Administration (NHTSA), and Evenflo Company Inc. announced a recall of Evenflo embrace infant car seat/carriers because of a malfunctioning handle (*CNNMoney* 2007). The well-publicized recall of Toyota in 2009 highlights that product recalls can affect a significant proportion of drivers and that the defects connected with them can result in loss of life and serious accidents.

Recalls of hazardous products reflect a lack of quality assurance in the firm's operations (Barber and Darrough 1996; Chao, Iravani, and Savaskan 2009). Although the goal of product recall programs is to solve potential safety problems, little is known about whether firms respond to product recalls beyond withdrawing and repairing the defective products. While there is some evidence to suggest that firms seek to improve reliability following external failures (Chao, Iravani, and Savaskan 2009; *Ward's Auto World* 1997), there are also reports indicating that firms are skeptical about the merits of the product recall program. For example, as a business report from more than two decades ago notes, "General Motors has been trying to persuade the Federal Government that it isn't dangerous if the rear wheel and axle fall off, in an effort to avoid a recall" (*The Wall Street Journal* 1983, p. 2). Understanding whether firms improve product reliability after product recalls is critical because consumers' uncertainty about the quality of the firm's offerings tends to increase in the wake of product recalls (Zhao, Zhao, and Helsen 2011) and in turn affects purchase decisions (J.D. Power and Associates 2004). Similarly, although regulatory agents contend that product recalls are beneficial because they reduce the harm caused by hazardous products, there is no systematic evidence to support this contention. An understanding of whether and how product recalls influence learning outcomes for firms in the future is thus valuable from a managerial and public policy perspective.

The objective of this study is to investigate whether and how product recalls reduce the number of accidents and recalls in the future. We argue that the benefits of product recalls (i.e., lower number of accidents and recalls) accrue because of improvements in product reliability. The contributions of this study to the product recall literature are threefold. First, we provide an empirical test of the direct effects of product recalls on future accidents and future recalls and indirect effect through future product reliability.

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Although previous research in marketing, economics, and strategic management has investigated the impact of product recalls on learning and performance outcomes (for an overview, see Table 1), there is no research that has tested the impact of product recalls on subsequent product reliability. Previous research has examined how prior recall experience or production experience of firms might lead to reduction in future recalls (Haunschild and Rhee 2004; Thirumalai and Sinha 2011). These studies, nonetheless, recognize improvement in product reliability as a potential route through which such effects manifest. For example, Thirumalai and Sinha (2011, p. 382) note that "learning across these aspects increases with cumulative recall experience, and, in turn, could lead to improved product quality and a reduction in the likelihood of quality failures over time." However, it is not clear if prior cumulative recall experience or production experience necessarily translates into more reliable products. As Levin (2000, p. 632) notes, "Learning in the quality domain is likely to come not so much from how many cars have gone down the assembly line, but from the intensity of 'off-line' activities." Direct evidence on whether product recalls improve reliability and, in turn, lower the number of accidents and recalls in the future enriches the increasing literature in this area and will help researchers better assess the efficacy of product recalls.

Second, we test the contingent role of firm ability in influencing the learning efforts after recalls. Extant research recognizes that not all firms learn equally and that the magnitude of learning depends on factors related to the ability of the firm to learn (Boulding and Staelin 1995; Cyert and March 1963; Greve 1998). In the context of product recalls, the firm's shared product assets—that is, the extent to which products in the family share assets (e.g., parts/components, design, manufacturing facilities)—are likely to be an important boundary condition for learning. Sharing of product assets has an impact on the firm's cost structure and market performance (Hauser 1999; Krishnan and Gupta 2001; Ramdas 2003). The relevance of examining this moderator is underscored in Toyota's well-publicized recall in 2009, which led to speculations of whether approaches that emphasize knowledge sharing are detrimental to quality assurance in the automobile industry. The findings of this study suggest that firms with greater sharing of product assets achieve greater improvement in product reliability after product recalls than firms with lower sharing of product assets.

Third, we test how the prior quality of the brand involved in the recall influences improvement in reliability after a product recall. "Prior brand quality" refers to the consumer's existing perceptions of the overall quality of the brand (Aaker and Jacobson 1994). The rationale for examining prior brand quality as a moderator stems from extant research that emphasizes the importance of motivational factors in influencing the learning efforts of firms (Boulding and Staelin 1995; Cyert and March 1963; Greve 1998). Previous research on product recalls has examined the impact of brand reputation before the recall crisis on subsequent performance (Cleeren, Dekimpe, and Helsen 2008; Rhee and Haunschild 2006). However, relatively less is known about the role of prior brand quality in improving reliability after a recall. Our findings offer insight into this issue and suggest that brands with lower prior quality improve product reliability to a greater extent after a recall than brands with higher prior quality.

We chose the automobile industry as our empirical context because this sector is of considerable economic significance. For example, the automobile business represents more than 3% of the U.S. gross domestic product and accounts for one in seven jobs in the U.S. domestic economy (Pauwels et al. 2004). Importantly, the automobile industry has witnessed a bevy of product recalls, which allows us to longitudinally examine their impact on reliability and market accidents. Furthermore, analysts and regulators have closely scrutinized this industry. In summary, by focusing on a single industry, we are able to enhance the internal validity of the study and provide actionable insights into an important and crucial sector of the U.S. economy.

We organize the rest of the article as follows: First, we provide a brief overview of the organizational learning literature and present our research hypotheses. This is followed by a description of the cross-sectional time-series data, the methodology, and the variables used in the study. Next, we present the results and briefly discuss their robustness to alternate models and measures. Finally, we discuss the theoretical and managerial implications of our study.

Conceptual Framework and Hypotheses

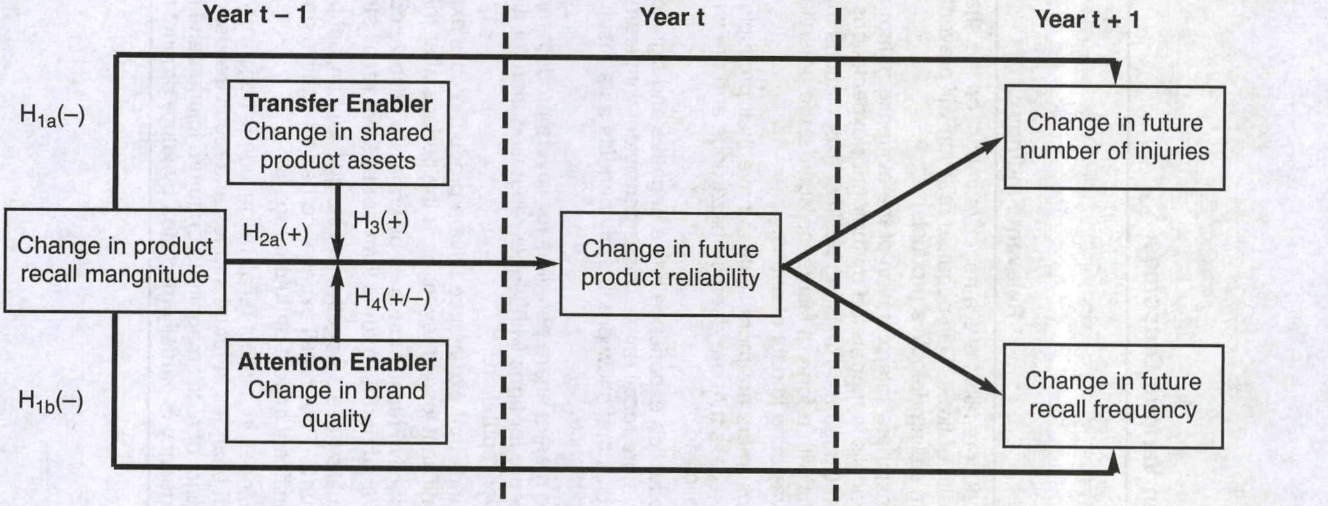
Organizational learning has been conceptualized in numerous ways in previous research (for reviews, see Levitt and March 1988; Moorman and Miner 1997; Sinkula 1994). Our conceptualization of learning mirrors the behavioral view of the theory of the firm. Here, learning is represented as emanating from the organization's experience in a path-dependent way and becoming encoded in routines (e.g., rules, standard operating procedures) (Cyert and March 1963; March 1991). If performance does not meet aspiration levels, problem-driven search occurs. In some situations, external events such as product recalls could induce learning (Haunschild and Rhee 2004). Therefore, learning in organizations is characterized by the institutionalization of routines and is punctuated by external disruptions such as product recalls. In this tradition, learning occurs when there is a perceptible or noticeable change in behavior.

Building on these perspectives, we develop a conceptual model that delineates the direct impact of product recall magnitude at time $t - 1$ on future number of accidents and future number of recalls at time $t + 1$ and indirect impact through future product reliability at time t. Figure 1 presents our conceptual model. It is well recognized in the organizational learning literature that the extent to which firms learn depends on their ability and motivation to do so (Boulding and Staelin 1995; DiMaggio and Powell 1983; Greve 1998). Consistent with this stream of research, we identify "transfer enablers" and "attention enablers" as contingency factors for improvement in product reliability. We posit that the firm's shared product assets are likely to enable the transfer of learning to various products in the family (i.e.,

TABLE 1
Overview of Previous Research on Product Recalls and Its Impact on Various Outcomes

Studies	Firm Performance (Sales, Market Share, and Stock Market Reactions)	Future Recall Rates	Consumer Responses	Market Accidents	Product Reliability	Relevant Findings
Jarrell and Peltzman (1985)	✔	X	X	X	X	Product recalls have a negative impact on the shareholder wealth of firms. This negative reaction will prevent managers from selling defective products.
Dawar and Pillutla (2000)	X	X	✔	X	X	Consumers' interpretation of the evidence of firm response to recalls is moderated by their prior expectations about the firm. Consumers' existing positive expectations may provide firms with a form of insurance against the potentially devastating impact of crises.
Rupp and Taylor (2002)	X	X	✔	X	X	Consumers are more likely to have their products repaired for recalls that are deemed hazardous and are well publicized.
Haunschild and Rhee (2004)	X	✔	X	X	X	Production experience has a negative and significant impact on future recall rates. This is consistent with learning curve studies that show productivity benefits as a result of experience.
Rhee and Haunschild (2006)	✔	X	X	X	X	The market share penalties for severe product recalls are steeper for firms with higher reputation than for firms with lower reputation.
Van Heerde, Helsen, and Dekimpe (2007)	✔	X	X	X	x	Brands that experience severe product recalls experience a significant loss in revenues in the periods after the crisis.
Chen, Ganesan, and Liu (2009)	✔	X	X	X	X	Proactive recall strategies by firms are associated with lower abnormal returns than are passive recall strategies.
Thirumalai and Sinha (2011)	✔	✔	X	X	X	Recalls have a negative but insignificant impact on abnormal returns. Prior recall experience has a negative and significant impact on future recalls.
The current study	X	✔	X	✔	✔	Changes in product recall magnitude is negatively associated with changes in future injuries and recall frequency. The impact of recall magnitude on future injuries and recall frequency is partially mediated by future product reliability.

FIGURE 1
A Conceptual Model of Product Recalls, Future Product Reliability, Future Accidents, and Future Recall Frequency



transfer enabler). Accordingly, the conceptual model depicts shared product assets as a moderator of the relationship between product recall magnitude and future product reliability. Similarly, we posit that the extent to which firms attend to the recall depends on the quality of the brand involved in the recall. This, in turn, would alter the motivation of firms to learn from product recalls (i.e., attention enabler). Accordingly, we propose that prior brand quality moderates the relationship between product recall magnitude and future product reliability.

Product Recall Magnitude and Learning Outcomes

Product recalls can be viewed as a manifestation of the firm's failure to provide a safe product to the market. It is known that failures are often an opportunity for firms to learn (Haunschild and Sullivan 2002; Miner et al. 1999). However, not all failures influence firm learning. The ability and motivation to learn from failures depend on the magnitude of the product recall. We expect firms to learn more from product recalls of larger magnitude than from product recalls of smaller magnitude. This is because smaller recalls carry the danger of being dismissed without due attention or being viewed as an aberration.

Large product recalls serve as a catalyst to stimulate learning in firms (Argote 1999; Levinthal and March 1993). The organization's response to product recalls could encompass a wide range of behaviors. A mandated response involves firms withdrawing defective products from the marketplace and repairing them. However, the impact of this response is limited to the defective products. Alternately, firms learn through a root cause analysis by developing a complex understanding of the association between the causes and effects of the product recall. Empirical evidence from previous research supports this view and suggests that firms learn from product recalls and reduce the number of future product recalls (Haunschild and Rhee 2004; Thirumalai and Sinha 2011). The scope of such learning is broader as firms aim to eliminate problems that led to the recall. If so, such learning should result in significantly lowering the number of injuries and also the number of recalls in the marketplace. In contrast, because larger product recalls serve as a catalyst for learning, the improvement in learning outcomes when there are smaller product recalls is not likely to be substantial. In line with these arguments, we expect that product recalls of larger magnitude are likely to lower the future number of injuries and future recall frequency to a greater extent than product recalls of smaller magnitude. Thus:

> H_1: Increases in recall magnitude lead to decreases in (a) future number of injuries and (b) future recall frequency.

Product Recall Magnitude and Learning Outcomes: The Product Reliability Pathway

Product recalls are a reflection of a lack of quality control or quality assurance in firm operations (Barber and Darrough 1996; Chao, Iravani, and Savaskan 2009). "Product reliability" refers to the objective measure of the total number of defects for a product. As we noted previously, previous research has suggested that stock markets react negatively to product recall announcements because it signals lack of reliability. That is, product recalls not only impose significant direct costs for the firm but also jeopardize its future prospects because it has questionable product reliability (Barber and Darrough 1996; Chen, Ganesan, and Liu 2009). Previous research has used cumulative production experience (Haunschild and Rhee 2004) or prior recall experience as proxies for learning and future quality improvements after product recalls (Thirumalai and Sinha 2011). Chao, Iravani, and Savaskan (2009) use a stylized analytical model to understand the normative contract structures between manufacturers and suppliers that affect quality improvement efforts after a product recall debacle such that potential problems are detected and eliminated early.

Why do firms improve reliability after product recalls and not before them? Firms typically have economic incentives to reduce costs, but they do not always have an incentive to improve product reliability (Levin 2000). When firms do not experience any product failures, it induces them to ignore information and leads decision makers to be overconfident about the adequacy of existing knowledge. Firms may not improve reliability in the absence of recalls because performance may not fall below aspiration levels (Cyert and March 1963). In such cases, firms may persist with product reliability levels that are above a certain predetermined threshold. Large product recalls serve as a catalyst in initiating improvements in product reliability that are typically expensive to implement (Argote 1999; Levinthal and March 1993). This should direct the organization's and/or its supplier's attention to potential problems and induce a search for fixing product defects. It is known that the greatest improvements in product reliability occur during certain windows of opportunity rather than during the production life (Levin 2000; Tyre and Orlikowski 1994). A large recall is one of those windows for firms to either develop new routines or change existing routines. Because product reliability is a leading indicator of product safety (Murthy, Rausand, and Østerås 2008), improved product reliability should in turn lower the subsequent number of injuries and recalls. In line with these arguments, we advance the following hypotheses:

> H_2: (a) Increases in recall magnitude lead to increases in future product reliability. Product reliability mediates the impact of recall magnitude on (b) future number of injuries and (c) future recall frequency.

Product Recall Magnitude and Future Product Reliability: The Moderating Role of Shared Product Assets

The preceding discussion assumes that all firms learn equally and improve product reliability after product recalls of large magnitude. This is unrealistic, in that the ability to improve reliability might vary according to the firm's resource endowments. A factor that aids or inhibits learning from product recalls is the firm's shared product assets. "Shared product assets" refer to the extent to which firms share assets (e.g., parts or components, manufacturing plants) across the product family. In several industries (e.g., semiconductors, computers, automobiles), the product design and manufacturing efforts are focused on sharing and combining knowledge across the product family (for excellent reviews, see Krishnan and Gupta 2001; Meyer and Utterback 1992). Sharing of assets lowers the fixed costs of manufacturing and reduces time to market for new products.

However, the extent to which assets are shared across products varies considerably across firms. We argue that the firm's shared product assets play a significant role in enabling firms to improve product reliability. At higher levels of shared product assets, firms should be able to transfer the learning from recalls in a product type to other products in the family. The ease with which knowledge can be transferred from product recalls is also contingent on whether units that share knowledge have a similar culture (Argote 1999; Szulanski 1996). Thus, there should be relatively greater sharing of assets from product recalls across products in the same family because they are more likely to have similar cultural norms and values. If so, the potential flaws in design and/or manufacturing processes are likely to be identified and eliminated not just for the defective products but also for other products in the same family. Thus, the ability of firms to improve reliability should be greater if there is greater sharing of product assets. In contrast, at lower levels of shared product assets, the ability to transfer learning is constrained because the knowledge bases of products in the family may be sticky and idiosyncratic. In such situations, firms may not be able to improve product reliability significantly after a product recall. Thus:

> H_3: The positive relationship between recall magnitude and future product reliability is stronger for firms with more shared product assets than for firms with fewer shared product assets.

The Impact of Product Recall Magnitude on Future Product Reliability: The Role of Prior Brand Quality

The extent to which firms are motivated to learn from product recalls is likely to depend on the prior quality of the brands involved in the recall. "Prior brand quality" refers to the consumer's existing perceptions of the overall quality of the brand (Aaker and Jacobson 1994). This construct is conceptually distinct from product reliability in that the former is based on subjective judgments of the brand and the latter is based on objective accounts of product performance (for reviews, see Golder, Mitra, and Moorman 2012; Mitra and Golder 2006).

The arguments for how prior brand quality might influence the motivation of firms to improve reliability after product recalls are conflicting and equivocal. One school of thought suggests that high-quality brands are likely to be more motivated than low-quality brands to respond and improve reliability after a product recall. This is because in comparison with low-quality brands, high-quality brands are more likely to compete in the marketplace on the basis of differentiation (Aaker 2004; Mizik and Jacobson 2008; Schmalensee 1982). Product recalls are likely to erode the differentiation advantages of higher-quality brands (Rhee and Haunschild 2006). Therefore, brands of higher prior quality are likely to be more motivated to improve reliability and restore their differentiation advantage. Another school of thought contends that prior brand quality might insulate the firm from adverse stakeholder reactions to negative events (Cleeren, Dekimpe and Helsen 2008; Dawar and Pillutla 2000; Mitra and Golder 2006). If so, product recalls of brands with higher quality might be viewed as an aberration or be attributed to circumstances beyond the firm's control. This confirmatory bias might lower the motivation of high-quality brands to improve product reliability after recalls. Given the presence of equivocal arguments for the moderating effect of prior brand quality, we propose a nondirectional hypothesis:

> H_4: The positive relationship between recall magnitude and future product reliability is stronger or weaker for brands with higher prior quality than for brands with lower prior quality.

Research Methodology

Data and Measures

The empirical context for the study is the U.S. automobile industry. We assembled the data from several sources. We collected data on product recalls from the NHTSA, a federally governed organization established under the Highway Safety Act of 1970 with the goal of enhancing and monitoring highway and motor vehicle safety. Consistent with previous research (see Haunschild and Rhee 2004; Pauwels et al. 2004), we focus on the automaker (e.g., Acura, Lexus) as the unit of analysis. This is because these automakers are independent and assume responsibility for decisions on the recall process rather than being managed by their parent brand. Our sample comprises 27 makes of 14 automobile firms (BMW, Chrysler, Daimler AG, Ford, General Motors, Honda, Hyundai, Mazda [joint venture with Ford], Mitsubishi, Nissan, Porsche, Fuji Heavy Industries, Toyota, and Volkswagen) between 1995 and 2011. The makes in the sample are Chrysler, Dodge (parent firm: Chrysler or Daimler AG), Ford, Jaguar, Lincoln, Mercury, Volvo (parent firm: Ford), Buick, Cadillac, Chevrolet, Pontiac, Saab (parent firm: General Motors), Honda, Acura (parent firm: Honda), Toyota, Lexus (parent firm: Toyota), Nissan, Infiniti (parent firm: Nissan), Audi, Volkswagen (parent firm: Volkswagen), Mercedes-Benz (parent firm: Daimler AG), Porsche (parent firm: Porsche), BMW (parent firm: BMW), Hyundai (parent firm: Hyundai), Mazda (parent firm: Mazda Motor Corporation), Mitsubishi (parent firm: Mitsubishi), and Subaru (parent firm: Fuji Heavy Industries). The sample is representative; these 27 makes contribute to approximately 95% of the total industry sales of passenger cars in the United States.

The NHTSA maintains a database that includes every vehicle safety recall issued from 1966 on. A typical recall notice provides information on the vehicle make and models likely to be affected, the number of units recalled, and the nature of the defect. Recall magnitude, or the number of vehicles recalled, is influenced in part by the number of vehicles the make has on the road. To account for scale effects, we normalized the number of vehicles recalled in each year by the make's sales in the previous year. Our balanced panel of 459 make/year observations (27 makes × 17 years) includes 384 make/years when recalls occurred as well as 75 make/years when recalls did not occur; including both types of make/years obviates the need to assemble a control sample. In other words, each make serves as an implicit control for itself. This benefit makes panel data well suited for drawing causal inferences in comparison with purely cross-sectional designs (for an excellent review, see Baltagi 2005).

We used scores from the Initial Quality Study (IQS) developed by J.D. Power and Associates to operationalize product reliability. These annual scores reflect the number of problems consumers report for every hundred vehicles after 90 days of ownership. We reverse-coded the scores for ease of interpretation; thus, higher scores imply higher product reliability. We assembled the data on vehicle accidents from the Fatality Analysis Reporting System (FARS) maintained by NHTSA. The FARS requirement is part of a legislative package that requires manufacturers to report to NHTSA information on deaths and injuries because of potential safety defects. This data source enables us to isolate injuries attributable to vehicle-related problems and exclude accidents that occurred due to driver-related problems. Again, we normalized this variable by the sales of the make in the previous year.

To operationalize shared product assets, we collected data on four indicants: (1) the number of manufacturing plants used by the make,[1] (2) the number of platforms used by the make,[2] (3) the range of engine sizes offered by the make, and (4) the number of models offered by the make. We procured data on the number of manufacturing plants and the number of platforms used by the make from ELM Analytics, a vendor that tracks the supply chain of major U.S. automakers. We assembled the data on the automaker's engine sizes and number of models from publicly available sources such as *Automotive News*, company websites, and news archives. These four indicants reflect the extent to which firms would be able to transfer learning across various products in the family. Lower (higher) scores on these indicants imply greater (lesser) sharing of product assets. For example, an automaker with fewer manufacturing plants, fewer platforms, a narrower range of engine sizes, and fewer models implies greater sharing of product assets. Because the range and spread of scores on each of these indicants is different, we computed z scores for each indicant by make and year. The sum of z scores on the four indicants is our measure of shared product assets (for an alternate measure, see the section "Validation Analyses"). We reverse-coded the measure for ease of interpretation; therefore, higher (lower) z scores reflect higher (lower) levels of shared product assets.[3]

We procured data on brand quality from the EquiTrend study by Harris Interactive (formerly Total Research Corporation), a vendor that tracks the attributes of approximately 1200 brands across 46 product categories. The data are compiled by surveying more than 20,000 respondents each year. Brand quality is operationalized using a single-item scale: "Rate the overall quality of each brand using a 0 to 10 scale" (0 = "unacceptable/poor quality," 5 = "quite acceptable quality," and 10 = "outstanding/extraordinary quality").

We also collected data on several control variables. We collected the data on annual automakers' sales from the *Ward's Automotive Yearbook*, data on automakers' annual advertising expenditures from *Adweek*, and gas prices from Bureau of Labor Statistics. It is plausible that product reliability is influenced by the firm's financial slack and financial performance. Firms with greater financial slack and better

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

[2]A product platform refers to the "collection of assets [i.e., components, process, knowledge, people, and relationships] that are shared by a set of products" (Robertson and Ulrich 1998, p. 20).

[3]The measure of shared product assets for make i at time t is given by $Z^{4}_{k=1}(D^{MEAN}_{kt} - D_{ikt})/D^{SD}_{kt}$, where k represents a given component, and D^{MEAN}_{kt} and D^{SD}_{kt} represent the mean and standard deviation of the score of component k at time t.

financial performance are likely to have more resources at their disposal to allocate to reliability improvement initiatives (Modi and Mishra 2011; Nohria and Gulati 1996).[4] We operationalized financial slack in terms of cash reserves (Voss, Sirdeshmukh, and Voss 2008) and financial performance in terms of return on assets (Modi and Mishra 2011). We collected data on cash reserves, net income, and total assets from Compustat and annual reports of firms.[5] Table 2 summarizes the data sources and variable operationalization.

Data Setup and Lag Structure

A rigorous test of our hypotheses requires a close alignment of the theory, measures, and empirical model. We followed two steps to achieve this. First, we model the impact of recall magnitude in time period t – 1 on reliability in time period t and injuries and recall frequency in time period t + 1. The temporal separation enables us to test the hypothesized chain of events after a recall. Second, we classified the year of product recalls according to whether they occurred in the first or second half of the year. To illustrate, if a recall occurred in January 2004 (i.e., first half of 2004), we coded the recall as occurring in 2004. However, if a recall occurred in November 2004 (i.e., second half of 2004), we coded the recall as occurring in 2005.[6] This classification implies that the time window between the recall and future product reliability (i.e., product reliability in the following year) is between 6 and 18 months. The product recalls of makes in the sample are evenly distributed between the first and second half of the year. Thus, on average, there is a 12-month time window between product recalls and subsequent reliability. In summary, our data setup and lag structure (1) ensures that there is sufficient time lapsed after product recalls for firms to learn and improve reliability and (2) allows the results to be interpreted as Granger causality.

Model Specification

Recall magnitude (t – 1) → future reliability (t). First, we test the impact of product recall magnitude on subsequent product reliability using the following specification:

$$\begin{aligned}(1)\quad \text{Model 1a}: \text{RELABL}_{ijt} &= \alpha_0 + \alpha_1\text{RECMAG}_{ijt-1} \\ &+ \alpha_2\text{SHARE}_{ijt-1} + \alpha_3\text{BQUAL}_{ijt-1} \\ &+ \alpha_4\text{RECMAG}_{ijt-1} \times \text{SHARE}_{ijt-1} \\ &+ \alpha_5\text{RECMAG}_{ijt-1} \times \text{BQUAL}_{ijt-1} \\ &+ \alpha_6\text{SLACK}_{jt-1} + \alpha_7\text{PERFM}_{jt-1} \\ &+ \alpha_8\text{RELABL}_{ijt-1} + \eta_i^{1a} + \theta_j^{1a} + \varepsilon_{ijt},\end{aligned}$$

where i = make, j = firm, t = year, α are the response coefficients, and ε is the random error component. The terms RELABL, RECMAG, SHARE, and BQUAL refer to reliability, recall magnitude, shared product assets, and prior brand quality, respectively. The terms SLACK and PERFM refer to financial slack and firm performance, respectively. We also include the lagged dependent variable in this specification to capture reinforcement effects (Dekimpe and Hanssens 1999) and to facilitate interpretation of the effects as Granger causality (for a similar approach, see Boulding and Staelin 1995). We performed Hausman's test to evaluate the appropriateness of random-effects versus fixed-effects estimators. Treating the unobserved effects as random is tantamount to assuming that the unobserved effects are uncorrelated with the explanatory variables. If this assumption is not met, random-effect estimates are biased and inconsistent (Baltagi 2005). The Hausman's specification test suggests that random-effect estimates are not consistent ($\chi^2 = 36.84$, d.f. = 7, $p < .01$). Therefore, we include make (η_i) and firm (θ_i) dummies in the specification.

It is plausible that prior brand quality at time t – 1 might be determined by product reliability and recall magnitude from time periods t – 1.[7] We resolve this potential endogeneity using instrumental variable techniques. We use advertising expenses scaled by sales (ADV) as an instrument for the endogenous prior brand quality variable. Advertising expenses is an appropriate instrument in this context because although it is expected to positively affect brand quality (Mitra and Golder 2006), it is unlikely to influence product reliability, which is based on objective product performance. To resolve this endogeneity, we estimated a regression model with prior brand quality as the dependent outcome and advertising expenses as the independent variable and used the predicted value of prior brand quality ($\text{BQUAL}^{\text{PRED}}$) from this regression in Model 1a.[8] Because the advertising expenses instrument is exogenous to the system, using predicted scores enables us to have exogenous variation in brand quality.

We transform Model 1a into a change specification by applying the first-differencing operator. The advantage of first-differencing is that it eliminates unobserved effects (see Boulding and Staelin 1995; Kim and McAlister 2011; Mizik and Jacobson 2007) and avoids the spurious regression problem (Granger and Newbold 1974).[9] Model 1a transforms to

$$\begin{aligned}(2)\text{Model 1b}: \Delta\text{RELABL}_{ijt} &= \alpha_1\Delta\text{RECMAG}_{ijt-1} \\ &+ \alpha_2\Delta\text{SHARE}_{ijt-1} + \alpha_3\Delta\text{BQUAL}^{\text{PRED}}_{ijt-1} \\ &+ \alpha_4\Delta\left(\text{RECMAG}_{ijt-1} \times \text{SHARE}_{ijt-1}\right) \\ &+ \alpha_5\Delta\left(\text{RECMAG}_{ijt-1} \times \text{BQUAL}^{\text{PRED}}_{ijt-1}\right) \\ &+ \alpha_6\Delta\text{SLACK}_{ij} + \alpha_7\Delta\text{PERFM}_{jt} \\ &+ \alpha_8\Delta\text{RELABL}_{ijt-1} + \lambda_t^{1b} + \Delta\varepsilon_{ijt},\end{aligned}$$

where the Δ operator refers to the first-differencing of the variable (for, e.g., $\Delta\text{RELABL}_{ijt}$ = RELABL_{ijt} –

[4]We thank an anonymous reviewer for this suggestion.

[5]There are three makes in our sample that changed ownership in the time period we examine (i.e., Jaguar, Volvo, and Saab). In these cases, we assembled data on control variables such as financial slack and return on assets from the parent firm at the time of ownership.

[6]We thank the area editor for this suggestion.

[7]We thank an anonymous reviewer for this suggestion. Our treatment of prior brand quality as endogenous implies that our structural model includes an equation for prior brand quality. In the interest of brevity, we do not formally state this equation.

[8]We checked the order and rank condition for this model and find the model to be identified.

[9]We thank the area editor and an anonymous reviewer for this suggestion.

TABLE 2
Variable Operationalization and Data Sources

Measure	Variable Name	Operationalization	Level of Aggregation	Data Sources
Recall magnitude	RECMAG	Number of vehicles recalled normalized for the number of passenger cars sold by the make in the previous year	Make, annual	NHTSA
Product reliability	RELABL	Number of problems per hundred vehicles (reverse coded for interpretation)	Make, annual	J.D. Power and Associates' IQS
Recall frequency	RECFRQ	Number of times in a year that a make recalls vehicles in a year	Make, annual	NHTSA
Injuries	INJ	Number of vehicle related injuries for the recalled make normalized for every million sold by the make in the previous year	Make, annual	FARS maintained by NHTSA
Prior brand quality	BQUAL	Single item measure on "Rate the overall quality of each brand using a 0 to 10 scale, where 0 implies 'Unacceptable/Poor quality, 5 implies 'Quite acceptable quality,' and 10 implies 'Outstanding/ Extraordinary quality'"	Make, annual	Harris Interactive
Shared product assets	SHARE	Composite standardized Z score on four components: the number of manufacturing plants, the number of platforms, range of engine sizes, and the number of models	Make, annual	ELM Analytics, *Automotive News*, annual reports, news reports
Advertising	ADV	Advertising expenses in dollars scaled by unit sales	Make, annual	*Adweek*
Sales	SALE	Number of units of the make sold	Make, annual	*Ward's Automotive Yearbook*
Gas price	GAS	Price per gallon in dollars	Annual	Bureau of Labor Statistics
Financial slack	SLACK	Cash and short-term investment (CHEQ)	Firm, annual	Compustat, annual reports
Financial performance	PERFM	Net income (NIQ)/total assets (ATQ)	Firm, annual	Compustat, annual reports

$RELABL_{ijt-1}$). Because the first-differencing accounts for make- and firm-specific time-invariant fixed effects, the terms η_i and θ_j are no longer needed in the preceding equation. To control for time-specific unobserved effects, we include dummies for year (λ_t). The lagged dependent variable in Model 1b ($\Delta RELABL_{ijt-1}$) is likely to be correlated to the random error. Consistent with previous research (McAlister, Srinivasan, and Kim 2007; Mizik and Jacobson 2007), we use the second lag (t – 2) of the dependent variable as an instrument for the lagged dependent variable. A test of H_{2a} requires the coefficient $\alpha_1 > 0$, a test of H_3 requires the coefficient $\alpha_4 > 0$, and a test of H_4 requires either $\alpha_5 > 0$ or $\alpha_5 < 0$.

Recall magnitude (t – 1) and reliability (t) → future injuries (t + 1) and future recall frequency (t + 1). We test the impact of recall magnitude and reliability on subsequent injuries and recall frequency using the following specifications:

$$(3)\text{Model 2a: } INJ_{ijt+1} = \beta_0 + \beta_1 RELABL_{ijt} + \beta_2 RECMAG_{ijt-1} + \beta_3 INJ_{ijt} + \eta_i^{2a} + \theta_j^{2a} + \xi_{ijt+1}, \text{ and}$$

$$(4)\text{Model 3a: } RECFRQ_{ijt+1} = \chi_0 + \chi_1 INJ_{ijt+1} + \chi_2 RELABL_{ijt} + \chi_3 RECMAG_{ijt-1} + \chi_4 RECFRQ_{ijt} + \eta_i^{3a} + \theta_j^{3a} + \zeta_{ijt+1},$$

where β and χ are the response coefficients and ξ and ζ are the random error components. We again include lagged dependent variables to capture reinforcement effects (Dekimpe and Hanssens 1999) and to allow the effects to be interpreted as Granger causality. As previously, we performed the Hausman test to determine the appropriateness of random-effects versus fixed-effects estimators for controlling unobserved heterogeneity. The Hausman specification test suggests that random effect estimates are not consistent for either the injuries equation ($\chi^2 = 32.98$, d.f. = 4, $p < .01$) or the recall frequency equation ($\chi^2 = 58.42$, d.f. = 4, $p < .01$). Thus, we use dummies (i.e., fixed effects) to control for make-specific (η_i) and firm-specific (θ_j) heterogeneity.

It is worth noting that in Model 3a, we expect recall frequency at time t + 1 to be influenced by the number of injuries at time t + 1. This is because firms may recall products on the basis of injuries occurring in the same time period to avoid the possibility of fines and lawsuits in the future. However, we do not expect recall frequency to influence injuries in the same time period, because these effects typically take longer to manifest. We resolve the endogeneity of injuries in Model 3a using instrumental variable techniques. We use gas prices (reverse coded for ease of interpretation) as an instrument for the endogenous injuries variable. This is an appropriate instrument, because while gas prices are expected to influence the number of injuries through vehicle usage, they are not likely to influence recall frequency.[10] We estimate a regression model with number of injuries as the dependent outcome and gas price as the independent variable, and we use the predicted values of injuries (INJ^{PRED}) from this regression in Model 3a. As previously, we transform Models 2a and 3a into a change specification through first-differencing. Models 2a and 3a transform to the following:

$$(5)\text{Model 2b: } \Delta INJ_{ijt+1} = \beta_1 \Delta RELABL_{ijt} + \beta_2 \Delta RECMAG_{ijt-1} + \beta_3 \Delta INJ_{ijt} + \lambda_t^{2b} + \Delta\xi_{ijt+1}$$

$$(6)\text{Model 3b: } \Delta RECFRQ_{ijt+1} = \chi_1 \Delta INJ_{ijt+1}^{PRED} + \chi_2 \Delta RELABL_{ijt} + \chi_3 \Delta RECMAG_{ijt-1} + \chi_4 \Delta RECFRQ_{ijt} + \lambda_t^{3b} + \Delta\zeta_{ijt+1},$$

where the Δ operator refers to the first-differencing of the variable. Again, first-differencing accounts for make- and firm-specific time-invariant fixed effects; thus, the terms η_i and θ_j are no longer needed in the preceding equations. In addition, to control for time-specific unobserved effects, we include dummies for year (λ_t). The lagged dependent variables in Models 2b and 3b are likely to be correlated with the random error. As previously, we use the second lag (t – 2) of the dependent variable as an instrument for the lagged dependent variable. A test of H_1 requires the coefficient $\beta_2 < 0$ and $\chi_3 < 0$. Similarly, a test of the mediation hypotheses, H_{2b} and H_{2c}, require the coefficients $\beta_1 < 0$ and $\chi_2 < 0$.

Last, there are a few econometric issues pertaining to the error structure in Models 1b, 2b, and 3b that need to be addressed. First, it is possible that first-differencing does not eliminate autocorrelation in Models 1b, 2b, and 3b because of the presence of the lagged dependent variable. We tested for first-order autocorrelation in each of these models. The F-statistic for the Wooldridge test for autocorrelation for Model 1b is 17.71 ($p < .01$), for Model 2b is 10.92 ($p < .01$), and for Model 3b is 13.15 ($p < .01$). This confirms the presence of first-order serial correlation. Second, because the data comprise 27 makes of 14 automobile firms, there is likely to be cross-sectional dependence between makes of the same firm. For example, the reliability of Acura and Honda are likely to be correlated. We test for cross-sectional dependence using the Breusch-Pagan Lagrange-multiplier test (Breusch and Pagan 1980). The chi-square statistics for this test for reliability, injuries, and recall frequency are 708.14 ($p < .01$), 238.57 ($p < .01$), and 622.88 ($p < .01$), respectively. These tests indicate that there is cross-sectional dependence in the data. Third, we tested for the presence of heteroskedasticity in the panel errors. The chi-square statistics for the Wooldridge's (2002) likelihood ratio test of heteroskedasticity for reliability, injuries, and recall frequency are 206.13 ($p < .01$), 324.88 ($p < .01$), and 108.25 ($p < .01$), respectively. These findings suggest the presence of panel-level heteroskedasticity in the errors of Models 1b, 2b, and 3b. Fourth, the errors in Model 2b and Model 3b may be correlated.[11] If so, seemingly unrelated regressions might increase the efficiency of the estimates. We

[10]We checked the order and rank condition for this model and find the model to be identified.

[11]Note that the error term in Model 1b (reliability) pertains to time period t, whereas those in Models 2b (injuries) and 3b (recall frequency) pertain to time period t + 1; thus, the error term of Model 1b is not likely to be correlated to those in Model 2b or 3b.

performed the Breusch-Pagan test to check for the dependence of the errors.[12] The chi-square statistic with one degree of freedom is 1.326 ($p > .10$). In addition, the bivariate correlation between the errors of Model 2b and Model 3b is –.017. Thus, the errors of Model 2b and Model 3b are independent, and three-stage least squares estimation will not yield more efficient estimates than two-stage least squares estimates.

In summary, the estimation must account for first-order serial correlation, cross-sectional dependence, and heteroskedasticity in Models 1b, 2b, and 3b. Following procedures advocated in previous research (Hanssens, Parsons, and Schultz 2003; Leeflang 2011), we use the iterative generalized least squares (IGLS) estimator and specify a heteroskedastic, spatially and serially correlated error structure (for an alternate estimator, see the "Validation Analyses" section).

Results

Overall Descriptive Findings

Table 3 presents the summary statistics and correlations between key variables in the study. The mean score for recall magnitude in the sample is .88. That is, the average number of passenger cars recalled by a make in a year is approximately 88% of the total number of cars sold by the make in the previous year. The average annual sales (in units) for makes in the data is 462,319 units. In addition, the average number of injuries for a make is 69.62 per million vehicles sold in the previous year. (Recall that these injuries pertain only to accidents due to vehicle related faults.)

Impact of Recall Magnitude on Future Number of Injuries and Recall Frequency: Results

H_{1a} and H_{1b} state that increases in recall magnitude will lead to decreases in future number of injuries and future recall frequency, respectively. As noted previously, we test the impact of changes in recall magnitude in year t – 1 on changes in the number of injuries and recall frequency in year t + 1.[13] We report these results in the second and third columns ("Direct-Effects Model") in Table 4. The coefficient for the impact of changes in product recall magnitude on changes in future number of injuries is negative and significant (–.879, $p < .01$). Similarly, the coefficient for the impact of changes in recall magnitude on changes in future recall frequency is also negative and significant (–.065, $p < .05$). Thus, H_{1a} and H_{1b} are supported, indicating that product recalls indeed have an effect in lowering the number of accidents and recalls experienced in future time periods.

Impact of Recall Magnitude on Future Product Reliability: Results

H_{2a} hypothesizes that increases in recall magnitude will lead to increases in future product reliability. The first column of Table 4 ("Indirect-Effects Model") reports the results for the impact of changes in recall magnitude in year t – 1 on changes in product reliability in year t (for detailed specification, see Equation 2). Consistent with H_{2a}, the coefficient for the impact of changes in recall magnitude on future changes in reliability is positive (.684, $p < .01$). We interpret this finding as indicative of learning because the reliability measure (i.e., the number of defects per hundred vehicles) is aggregated across all new models of the make in the following year (i.e., including models not affected by the recall).

H_{2b} and H_{2c} pertain to whether product reliability mediates the impact of recall magnitude on future injuries and future recall frequency. Consistent with our model specification (see Equations 5 and 6), we test the impact of

[12]The null hypothesis for the Breusch-Pagan test is that the errors are independent.

[13]In this model, we do not include the impact of product reliability at time t because we are primarily interested in the direct effects of recall magnitude. However, in the test of mediation, we estimate the total-effects model after including product reliability.

TABLE 3
Sample Summary Statistics

	M	SD	RECMAG	RELABL	SHARE	BQUAL	INJ	RECFRQ	SALE	GAS	ADV	SLACK
RECMAG[a]	.88	4.09										
RELABL[b]	276.66	28.15	.08									
SHARE[c]	0	3.48	.03	.01								
BQUAL	5.11	4.34	–.01	.32	.01							
INJ[d]	69.62	183.77	–.18	–.01	.00	–.07						
RECFRQ[e]	7.28	8.38	.21	–.15	.00	.03	.00					
SALE[f]	462,319	675,956	–.07	–.08	–.05	.19	–.03	.19				
GAS[g]	2.01	.76	.17	.07	.01	–.06	–.12	.02	–.09			
ADV[h]	1.15	1.20	–.04	–.03	–.04	.30	.00	.19	.78	.13		
SLACK[i]	144.94	835.90	–.02	.02	–.01	–.21	–.01	.14	–.02	.10	.07	
PERFM	.02	.11	.03	.09	.05	.03	.02	.02	–.06	–.06	.00	.02

[a]For every vehicle sold in the previous year.
[b]We reverse coded IQS scores for ease of interpretation. Higher scores on RELIABL imply greater reliability.
[c]The mean is zero because the SHARE measure represents Z scores.
[d]For one million vehicles sold in previous year.
[e]Number of recalls in a year.
[f]Units.
[g]Price is in dollars per gallon.
[h]In thousands of dollars per car sold.
[i]In millions of dollars.

TABLE 4
Impact of Recall Magnitude on Future Reliability, Future Injuries, and Future Recall Frequency

Dependent/Independent Variables	Reliability in Year t: $\Delta RELABL_{ijt}$ Indirect-Effects Model		Injuries and Recall Frequency in Year t + 1: ΔINJ_{ijt+1} Direct-Effects Model		$\Delta RECFRQ_{ijt+1}$ Direct-Effects Model	
Lagged Independent Variables						
Recall magnitude ($\Delta RECMAG_{ijt-1}$)	H_{2a}: .684***	(.219)	H_{1a}: −.879***	(.269)	H_{1b}: −.065**	(.028)
Shared product assets ($\Delta SHARE_{ijt-1}$)	−.169	(.163)				
Prior brand quality ($\Delta BQUAL^{PRED}_{ijt-1}$)	1.121	(1.060)				
Recall magnitude × shared product assets [$\Delta(RECALL_{ijt-1} \times SHARE_{ijt-1})$]	H_3: .025**	(.012)				
Recall magnitude × prior brand quality [$\Delta(RECALL_{ijt-1} \times BQUAL^{PRED}_{ijt-1})$]	H_4: −.106**	(.040)				
Reliability ($\Delta RELABL_{ijt-1}$)	−.101***	(.029)				
Injuries (ΔINJ_{ijt})			−.439***	(.128)		
Recall frequency ($\Delta RECFRQ_{ijt}$)					−.329***	(.063)
Controls						
Financial slack ($\Delta SLACK_{jt-1}$)	.006**	(.003)				
Financial performance ($\Delta PERFM_{jt-1}$)	5.802**	(2.636)				
Injuries ($\Delta INJ^{PRED}_{ijt+1}$)					.012*	(.007)
Year dummies	11 significant		8 significant		11 significant	
Chi-square (d.f.)	527.38	(21)	484.03	(15)	204.13	(16)

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Coefficient (SE).

changes in product reliability in year t on changes in injuries and changes in recall frequency in year t + 1. We report the results in columns 1 and 3 of Table 5 ("Indirect-Effects Model"). The coefficients for the impact of changes in product reliability on changes in future number of injuries (−1.346, $p < .05$) and changes in future recall frequency (−.077, $p < .05$) are negative and significant.

We use the sequential procedures Baron and Kenny (1986) advocate to test whether product reliability mediates the impact of recall magnitude on future injuries and recall frequency. We compare the coefficients for the impact of changes in recall magnitude in the direct-effects model (see Table 4) and the total-effects model (see Table 5). The direct-effects model tests for the direct impact of changes in recall magnitude on changes in future injuries and future recall frequency. The total-effects model tests for the direct impact of changes in recall magnitude on changes in future injuries and future recall frequency and indirect impact through changes in product reliability. We find that the coefficient for the impact of changes in recall magnitude on changes in future number of injuries is negative in the direct-effects model (−.879, $p < .01$) but smaller in magnitude in the total-effects model (−.764, $p < .01$). Similarly, the impact of changes in recall magnitude on changes in future recall frequency is negative in the direct-effects model (−.065, $p < .05$) but smaller in magnitude in the total-effects model (−.056, $p < .05$). This implies that the effects of product recalls (on future number of injuries and future recall frequency) manifest through the product reliability pathway. Following previous research (Steenkamp, Van Heerde, and Geyskens 2010), we computed the Sobel's test statistic for mediation analyses. The results suggest that the Sobel's statistics for the injuries model (−1.89, $p < .05^{\text{one-tailed}}$) and recall frequency model (−1.76, $p < .05^{\text{one-tailed}}$) are both significant. We also find that the fit of the total-effects model is significantly better than that of the direct and indirect-effects models. The difference in chi-square statistics for the injuries model ($\Delta\chi^2_{\text{total - direct}}(1) = 12.51$, $p < .01$, and $\Delta\chi^2_{\text{total - indirect}}(1) = 13.70$, $p < .01$) and the recall frequency model ($\Delta\chi^2_{\text{total - direct}}(1) = 14.30$, $p < .01$, and $\Delta\chi^2_{\text{total - indirect}}(1) = 13.42$, $p < .01$) are significant.

Following recent guidelines (Zhao, Lynch, and Chen 2010), we tested whether product reliability mediates the impact of recall magnitude on future accidents and future recall frequency using an alternate method.[14] To do so, we used bootstrapping procedures to generate an empirical sampling distribution for the indirect effects. In our case, the indirect effects are the product of the estimates of the (1) recall magnitude → reliability and reliability → injuries relationship and (2) recall magnitude → reliability and reliability → recall frequency relationship. After we drew 1000 bootstrap samples, we computed the indirect effect as the mean of the estimates from these samples. The 95% bootstrap confidence interval for the recall magnitude → reliability and reliability → injuries relationship is (−.96, −.08) and for the recall magnitude → reliability and reliability → recall frequency relationship is (−.07, −.003). Thus, the indirect effects are negative and significant in both cases. Collectively, we find support for our hypotheses that product reliability partially mediates the relationship between recall magnitude and future injuries (H_{2b}) and future recall frequency (H_{2c}).

[14]We thank the area editor for this suggestion.

TABLE 5
Impact of Reliability on Future Injuries and Future Recall Frequency

Dependent/Independent Variables	Injuries in Year t + 1 ΔINJ_{ijt+1} Indirect-Effects Model	Total-Effects Model	Recall Frequency in Year t + 1 $\Delta RECFRQ_{ijt+1}$ Indirect-Effects Model	Total-Effects Model
Lagged Independent Variables				
Recall magnitude ($\Delta RECMAG_{ijt-1}$)		–.764*** (.263)		–.056** (.025)
Reliability ($\Delta RELABL_{ijt}$)	–1.346** (.517)	–1.268** (.533)	–.077** (.035)	–.068** (.032)
Injuries (ΔINJ_{ijt})	–.514*** (.101)	–.350*** (.113)		
Recall frequency ($\Delta RECFRQ_{ijt}$)			–.306*** (.068)	–.322*** (.062)
Controls				
Injuries ($\Delta INJ^{PRED}_{ijt+1}$)			.010* (.006)	.016** (.008)
Year dummies	11 significant	9 significant	9 significant	8 significant
Chi-square (d.f.)	482.84 (15)	496.54 (16)	205.01 (16)	218.43 (17)

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Coefficient (SE).

H_3 posits that the positive relationship between recall magnitude and reliability is stronger for firms with higher shared product assets than for firms with lower shared product assets. As evidenced in Table 4, the coefficient for the interaction effect of recall magnitude and shared product assets on future reliability is positive and significant (.025, $p < .05$). Thus, H_3 is supported: firms that share product assets to a greater extent are able to transfer the learning from product recalls to models not affected by the recall and realize bigger improvements in reliability. We do not find the direct impact of shared product assets on reliability to be statistically significant ($p > .10$). Thus, there is no evidence to support conjectures that sharing of product assets adversely affects reliability.

To gain a deeper understanding of this interaction, we followed procedures advocated in previous research (Aiken and West 1991; Fitzsimmons 2008; Irwin and McClelland 2001) and performed a spotlight analysis.[15] Specifically, this analysis involves shifting the mean level of the moderator up and down by one standard deviation and testing for the significance of the slopes at these levels of the moderator. We conducted the spotlight analysis at one standard deviation above ("high shared product assets") and below the mean of the shared product assets variable ("low shared product assets"). The results suggest that the impact of recall magnitude on future product reliability at high levels of shared product assets is positive and significant (.329, $p < .05$) but insignificant at low levels of shared product assets ($p > .10$). We find the slopes to be significantly different across high and low levels of shared product assets (Δslope = .420, $p < .05$). This spotlight analysis again provides evidence to support H_3 and highlights the region in which this interaction effect manifests.

Recall that we proposed a nondirectional hypothesis for the moderating effect of prior brand quality on the recall magnitude–future reliability relationship (H_4). The results suggest that the coefficient for the interaction effect of recall magnitude and prior brand quality on future product reliability is negative and significant (–.106, $p < .05$). Thus, brands of higher prior quality are less motivated than brands of lower prior quality to improve product reliability following product recalls. This implies that brand quality might be a double-edged sword for firms when faced with product recalls. While higher brand quality might buffer firms from adverse stakeholder reactions to product recalls, this brand insulation effect also lowers firms' motivation to learn and improve reliability. In contrast, while lower-quality brands might be punished more for product recalls, they are likely to be more motivated to learn and improve reliability. The coefficient for the direct impact of prior brand quality on reliability is positive but not significant ($p > .10$).

As previously, we performed a spotlight analysis to gain deeper insights into this interaction effect. We examined the slope of the recall magnitude–future product reliability relationship at one standard deviation above ("high brand quality") and below ("low brand quality") the mean of the brand quality variable. The results suggest that the impact of recall magnitude on future product reliability is insignificant at high levels of brand quality ($p > .10$) but significant at low levels of brand quality (.985, $p < .05$). The difference in slopes across high and low levels of brand quality is statistically significant (Δslope = –.993, $p < .05$). This analysis again suggests that the motivation to improve reliability is greater for brands of lower quality than for brands of higher quality.

With regard to control variables, the results suggest that changes in financial slack is positively associated with future changes in product reliability (.006, $p < .05$). Similarly, changes in firm performance are positively associated with future changes in product reliability (5.802, $p < .05$). These findings are consistent with the view that greater resources at the firm's disposal help in implementing organizational changes (Cyert and March 1963; Greve 1998).

Validation Analyses

To assess the robustness of our empirical findings, we conducted a battery of additional tests. Specifically, we tested

[15]We thank the area editor for this suggestion.

the sensitivity of the results to (1) alternate measures of shared product assets, (2) alternate estimators, (3) using firm as the unit of analysis, and (4) alternate lag structures.

Alternate measure of shared product assets. As noted previously, we operationalized shared product assets using four indicants: (1) the number of manufacturing plants used by the make, (2) the number of platforms used by the make, (3) the range of engine sizes offered by the make, and (4) the number of models offered by the make. A potential concern about this measure is that some of the indicants (e.g., the number of manufacturing plants, the number of models of the make) might be correlated with the size of the make.[16] We examined the robustness of the results by operationalizing shared product assets using two alternate measures based on the subset of the four indicants. First, we dropped the number of manufacturing plants from the shared product assets measure and reestimated the results using this alternate measure. Second, we dropped both number of manufacturing plants and number of models from the shared product assets measure and reestimated the results using this measure. We report the results of these analyses in Table WA1 in the Web Appendix (www.marketingpower.com/jm_webappendix). As Table WA1 indicates, the substantive conclusions remain unchanged across these alternate measures of shared product assets. Thus, it is reasonable to conclude that the results are not an artifact of the measure used to operationalize shared product assets.

Alternate estimator. As noted previously, we estimated the results reported in the study using the IGLS estimator. We chose this method because we needed to account for first-order serial correlation, cross-sectional dependence, and heteroskedasticity in the errors. We assessed the robustness of the results to an alternate estimator, the panel-corrected standard error (PCSE) estimator, which is essentially a Prais-Winsten estimator. We report the results using this alternate estimator in Table WA2 in the Web Appendix (www.marketingpower.com/jm_webappendix). Table WA2 demonstrates that the estimates are similar to the estimates from IGLS, though the standard errors are slightly higher for the PCSE estimator. Importantly, the substantive conclusions of the study are the same regardless of whether an IGLS estimator or a PCSE estimator is used.

The firm as the unit of analysis. We assessed the robustness of the study's findings by using the firm rather than make as the unit of analysis.[17] As mentioned previously, our data comprise 27 makes from 14 major automobile firms. To reestimate the models, we aggregate all the make-level variables to the firm-level. Thus, we now have 238 firm-year observations (17 years × 14 firms) available for the empirical analysis. We excluded year-specific effects in this analysis to conserve degrees of freedom. We report the results of this analysis in Table WA3 in the Web Appendix (www.marketingpower.com/jm_webappendix). The results with firm as the unit of analysis are consistent with those reported for the make unit of analysis, though, as might be expected, the statistical significance for some of the findings is at marginally higher levels. Thus, this analysis provides additional support for our theoretical model and shows that the results are not sensitive to the chosen unit of analysis.

Alternate lag structures. Recall that we specified a one-year lag between recall magnitude, reliability, injuries, and recall frequency in our model specification. We assessed the appropriateness of this lag structure by comparing the fit statistics of models with several alternate lag structures. Following procedures advocated in previous research (Dekimpe and Hanssens 1999; Hanssens, Parsons, and Schultz 2003), we compared the Bayesian information criteria for the different model specifications. We report the results of this comparison in Table WA4 in the Web Appendix (www.marketingpower.com/jm_webappendix). We find that a model specification with one lag of the dependent variable and one lag of the independent variables (i.e., ADL(1,1)) offers the best fit (i.e., the lower the Bayesian information criteria, the better the model fit). Thus, a one-year time lag between the independent variables and dependent variables is appropriate in our context.

Discussion

Research has shown that the consequences of product recalls to firms as well as end customers are often significant. However, there is little evidence available regarding whether firms respond to product recalls (beyond removing and repairing the defective products). We develop and test research hypotheses that examine the impact of product recalls on future product reliability, number of injuries, and recalls in the future. Furthermore, we examine how shared product assets and brand quality pose boundary conditions, systematically affecting improvement in reliability after a recall. Next, we summarize our findings in relation to the research questions identified at the beginning of the article.

By examining the impact of recalls on outcomes such as product reliability, accidents, and recall frequency, our study makes the following contributions to the marketing literature. First, our study finds support for the idea that product recalls have a significant impact on improving safety by reducing number of injuries and recalls in the future. Previous researchers in marketing and strategic management have examined how stock markets react to product recalls and whether firms learn from product recalls and lower the number of future recalls (Chen, Ganesan, and Liu 2009; Haunschild and Rhee 2004; Thirumalai and Sinha 2011). There is also research that has examined when firms initiate recalls (Rupp and Taylor 2002) and when consumers are likely to respond to them (Dawar and Pillutla 2000; Rupp and Taylor 2002). While extant research on product recalls provides numerous valuable insights, there is little evidence regarding the impact of product recalls on accidents occurring in the marketplace. Our study contributes to the product recall literature by showing that product recalls work by lowering both accidents and future recalls in the marketplace.

[16]We thank the area editor and an anonymous reviewer for this suggestion.

[17]We thank the editor, area editor, and an anonymous reviewer for this suggestion.

Second, extant research has relied on the experience curve or learning curve paradigm and has argued that firms learn to reduce the incidence of recalls in the future (Haunschild and Rhee 2004; Thirumalai and Sinha 2011). The argument is that greater experience with production or product recalls should increase organizational knowledge, including the ability to detect errors and reduce the number of recalls in the future. However, there has been no direct test on whether product recalls enable firms to reduce product defects and enhance reliability. To the best of our knowledge, our study is the first to offer evidence that product recalls have a significant positive impact on product reliability. This study is a step toward beginning to better understand when firms are able and motivated to learn from product recalls and improve reliability.

Third, our study also identifies important boundary conditions for when firms are able and motivated to improve product reliability after product recalls. Our finding that improvement in reliability following recalls of large magnitude is higher for firms with greater sharing of product assets than for firms with lower sharing of product assets has important implications for research. Extant research in product management and operations research has examined the implications of sharing product assets on the firm's cost (i.e., economies of scale) and revenue (i.e., consumer's willingness to pay) structure (Cottrell and Nault 2004; Fisher, Ramdas, and Ulrich 1999; Hauser 1999). Our finding implies that product management researchers examining asset-sharing decisions should bear in mind the impact of these decisions on the ability of firms to respond to downstream processes such as product recalls. We also find that the motivation to improve reliability after product recalls is greater for brands of lower prior quality than for brands of higher prior quality. This is consistent with research that finds that higher-quality brands are blamed less for high incidence of product recalls (Cleeren, Dekimpe, and Helsen 2008; Dawar and Pillutla 2000; Tax, Brown, and Chandrashekaran 1998) but incongruent with research that expects that highly reputed brands would be blamed more for violating consumer expectations (Burgoon and LePoire 1993; Rhee and Haunschild 2006). Our study should encourage researchers to include brand quality as an important marketing variable in models examining firm learning from product recalls.

Managerial and Policy Implications

Our study offers valuable insights for managerial practice and public policy. Although the goal of product recall programs is to ensure safety, there is continued skepticism about the value of these programs. Some industry experts note that product recalls may actually increase the number of accidents in the marketplace, as the extra driving needed to attend to the recall increases the probability of accidents (McDonald 2009). Firms also decry that product recall programs have little societal benefit, in that accidents that occur in the marketplace are attributable to a host of other factors such as human error rather than vehicle faults. We find that large product recalls significantly reduce the number of injuries and the recall frequency in the future. We also show that the reduction in number of injuries and number of recalls is attributable in part to improvement in reliability after product recalls. The implication is that if firms learn broadly and improve reliability, they are likely to experience better outcomes in the future. In contrast, firms that restrict their response to attending to and fixing problems in defective vehicles without altering reliability are unlikely to witness a perceptible improvement in learning outcomes.

We performed a univariate transfer function analysis to better understand the economic implications of the findings (for details, see Hanssens, Parsons, and Schultz 2003). We computed the direct and indirect impact of a one standard deviation (SD) increase in recall magnitude on future product reliability, future number of injuries, and future recall frequency. Table 6 presents the results of this post hoc analysis. The results show that a one SD increase in recall magnitude results in future product reliability improving by 2.798 (at moderate levels of shared product assets) and by .582 (at moderate levels of brand quality). A one-SD increase in recall magnitude lowers the future number of injuries by 6.672 (at moderate levels of shared product assets) and by 3.863 (at moderate levels of brand quality). Similarly, we find that a one-SD increase in recall magnitude reduces the future number of recalls of makes by .419 (at moderate levels of shared product assets) and by .269 (at moderate levels of brand quality). Given that every additional injury and product recall imposes substantial direct and indirect costs on firms (e.g., lost goodwill) and society

TABLE 6
Post Hoc Analyses: Assessing the Managerial Relevance of the Findings

	Impact of a One-SD Increase in Recall Magnitude on		
Type of Effect	**Change in Future Reliability Direct**	**Change in Future Number of Injuries Direct + Indirect**	**Change in Future Number of Recalls Direct + Indirect**
Low shared product assets	2.257	–5.986	–.382
Average shared product assets	2.798	–6.672	–.419
High shared product assets	3.185	–7.163	–.446
Low brand quality	.773	–4.105	–.282
Average brand quality	.582	–3.863	–.269
High brand quality	.322	–3.533	–.251

Notes: Low, average, and high values are 25th, 50th, and 75th percentiles, respectively.

(e.g., health expenditures, lost productivity) (Blincoe et al 2002), evidence from our study should bolster support for the product recall program and its purported role in regulating public safety.

We caution that our finding that product reliability improves after product recalls (and in turn lowers future number of injuries and future recall frequency) does not imply that firms should engage in more recalls than what is already witnessed in the marketplace. The implication is that firms should perform careful premarket screening of products that might reduce the incidence of product failures. At present, premarket screening is not a priority, as firms often balance considerations of investing in reliability improvements with competing needs such as pursuing growth through new product introductions (Levin 2000).

Shared product assets as an enabler of learning. Our finding that sharing product assets enables firms to improve reliability more after larger recalls has important implications for managerial practice. The massive recall of Toyota in 2009 sparked a debate as to whether certain aspects of lean manufacturing such as sharing components, design, and plants across multiple models was responsible for the higher number of recalls witnessed in the industry (Wakabayashi 2010). The contention is that components and processes that are uniquely designed (and not shared) to fit a product are likely to be more reliable than components and processes that are designed to be shared by several products, which raises a managerially relevant question: Does sharing of product assets compromise product reliability? Our findings suggest that the direct effect of (changes in) shared product assets on (changes in) future reliability is not statistically significant ($p > .10$). Thus, concerns that greater sharing of product assets may be responsible for lapses in reliability in the automobile industry are not supported in our data. Importantly, our study indicates that when there is greater sharing of product assets, firms are able to improve reliability to a greater extent after product recalls.

We evaluate the difference in future reliability improvements between makes with high and low shared product assets through a transfer function analyses. We examine the impact of a one-SD change in recall magnitude on future change in reliability. The low and high values of shared product assets are set at the 25th and 75th percentiles of the variable, respectively. We find that, in response to a one-SD change in recall magnitude, the future reliability of makes with low shared product assets improves by 2.257, whereas the reliability of makes with high shared product assets improves by 3.185. Thus, makes with high shared product assets are able to improve reliability by approximately one point compared with makes with low shared product assets. Therefore, managers should plan for sharing of assets across products in the family so that they are able to learn and improve product reliability after product recalls. Our findings suggest that the difference in reliability improvement for firms with high versus low shared product assets is economically meaningful (i.e., one point change in reliability). It could be conjectured that improvement in reliability may partially restore investors' confidence in the firm and improve customer retention rates (Srinivasan et al. 2009). In the absence of shared product assets, firms are likely to find it difficult to improve product reliability after a recall.

Brand quality as an inhibitor of learning. Our findings highlight that the motivation of firms to improve reliability after product recalls varies depending on the brand's prior quality. We find that improvement in reliability after product recalls is higher for brands with lower brand quality than for brands with higher brand quality. The results in Table 6 reveal that a while a one-SD increase in recall magnitude results in the product reliability of lower quality brands improving by .773, the product reliability of higher quality brands improves by .322. It is plausible that the possibility of being penalized more for quality lapses motivates brands of lower prior quality to improve product reliability after a recall. This implies that there is a silver lining for firms with lower brand quality. Product recalls might benefit brands of lower quality by motivating them to improve product performance and in turn enhance their position in the marketplace. Further research could examine to what extent objective changes in quality alter perceptual or subjective quality. Our findings also caution brands of higher prior quality to be mindful of complacency traps that inhibit learning and deter reliability improvements after a product recall. Overcoming complacency is critical for brands of higher prior quality because the reluctance to improve product reliability after a recall might erode its competitive position in the marketplace in the long run.

Limitations and Conclusion

This study has some limitations that suggest areas for further research. The context for this study is the automotive industry, an important sector of the U.S economy. Although the firms and makes in the data are representative of the U.S. automotive industry, caution is warranted in generalizing the findings of this study to other contexts. A promising extension would be to test the conceptual framework in the consumer products category, another sector that has witnessed a spate of product recalls in the past decade or so. A recent CPSC development to consolidate injuries and deaths resulting from the use of hazardous consumer products could make this extension feasible.

This study focuses on the impact of product recalls of a make on learning outcomes for the same make. It would be worthwhile to investigate whether there are learning spillovers across makes of the same firm. For example, it might be worthwhile to examine whether product recalls of Pontiac (parent firm: General Motors) results in reliability improvement and lower accidents for Buick (parent firm: General Motors) and vice versa.[18] This does not impair the validity of our study's findings, because we empirically account for the possibility of learning across makes through a correlated error structure. Nonetheless, researchers could further examine this issue.

In summary, examining the effect of product recall magnitude on future learning outcomes enabled us to probe deeper into the learning "black box." The moderating role of shared product assets, a structural firm characteristic,

[18]We thank an anonymous reviewer for this suggestion.

provides new insights on when firms might be able to transfer their learning to other products in the family and respond better to product recalls. By examining the contingent role of prior brand quality, we demonstrate how the motivation of firms to learn and improve reliability might vary. We hope our study provides the impetus for more research on product recalls and their impact on reliability and learning outcomes in other empirical contexts.

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