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Online chatter is important because it is spontaneous, passionate, information rich, granular, and live. Thus, it can forewarn and be diagnostic about potential problems with automobile models, known as nameplates. The authors define "perverse halo" (or negative spillover) as the phenomenon whereby negative chatter about one nameplate increases negative chatter for another nameplate. The authors test the existence of such a perverse halo for 48 nameplates from four different brands during a series of automobile recalls. The analysis is by individual and panel vector autoregressive models. The study finds that perverse halo is extensive. It occurs for nameplates within the same brand across segments and across brands within segments. It is strongest between brands of the same country. Perverse halo is asymmetric, being stronger from a dominant brand to a less dominant brand than vice versa. Apology advertising about recalls has harmful effects on both the recalled brand and its rivals. Furthermore, these halo effects affect downstream performance metrics such as sales and stock market performance. Online chatter amplifies the negative effect of recalls on downstream sales by about 4.5 times.

Keywords: brand harm, online chatter, product recall, perverse halo, spillover

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Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?

Online chatter is spontaneous, passionate, widely available, low cost, granular, and live (Tirunillai and Tellis 2014). Furthermore, it affects consumer behavior because consumers have high trust in chatter from other consumers (Blackshaw and Nazzaro 2006). For example, 92% of consumers trust recommendations from friends and family more than any other form of advertising (Lithium 2014). Prior research has shown that online chatter is a leading indicator of sales (Asur and Huberman 2010; Dellarocas, Zhang, and Awad 2007; Liu 2006; Stephen and Galak 2012) and stock market performance (Luo 2009; Tirunillai and Tellis 2012). Moreover, online chatter is easier for firms to measure and monitor than traditional word of mouth (Tirunillai and Tellis 2012). The high visibility and impact of online chatter can be catastrophic for negative events. Classic examples include the iPhone antenna fiasco (Sorrel 2010), "Dell Hell" (Hof 2005), and "United Breaks Guitars" (Deighton and Kornfeld 2010). Indeed, researchers have found that bad news travels fast in social media and that negative chatter is more informative about firm performance than positive chatter (Chevalier and Mayzlin 2006; Kwak et al. 2010; Tirunillai and Tellis 2012).

Product recalls are one of the most frequent negative events that firms face in the current marketplace. Firms from various industries such as food, toys, automobiles, and drugs encounter product recalls. The number of product recalls has increased substantially over the past two decades and is likely to rise in the future (Dawar and Pillutla 2000). In 2010 alone, the

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National Highway Traffic Safety Administration (NHTSA) reports that more than 20 million vehicles were recalled. Recently, automobile recalls in 2014 reached a record of 63.5 million vehicles in 800 separate recall campaigns (Shepardson 2015). Such recalls may damage a firm's reputation, trust, and brand equity with consumers (Dawar and Pillutla 2000; Rhee and Haunschild 2006) and lead to losses in sales and market value (Chen, Ganesan, and Liu 2009; Chu, Lin, and Prather 2005; Cleeren, Dekimpe, and Helsen 2008; Rhee and Haunschild 2006; Van Heerde, Helsen, and Dekimpe 2007).

However, prior research on the effect of recalls on rival brands is very scarce (see Table A1 in Web Appendix A). Prior research on product recalls has mostly focused on the recalled firms. However, anecdotal evidence suggests that rival firms may be affected too. For example, after regional supermarkets in California voluntarily recalled specific lots of peaches, chatter in social network sites like Facebook alleged that food retail giants like Walmart, Costco, and Trader Joe's had similar issues.[1] Another recent study found that after Shuanghui Group recalled its meat products, consumers in online forums discussed a rival brand having similar issues (Yang and Yu 2014).

This study differs from prior studies in analyzing the effects of recalls in three ways. First, it focuses on the effect of recalls on online chatter aside from the effect on stock market returns and sales. Online chatter in social media sites is now an important piece of the product recall process. The Consumer Product Safety Commission (CPSC) has set up a social media guide for firms issuing recalls.[2] For example, firms should post the recall information (press release) on all social media outlets, such as Facebook, Pinterest, Google+, Instagram, and Twitter.

In addition, this study analyzes the effects of a recall at the daily level. Daily dynamics are critical because crises evolve from day to day, especially in the current age of digital diffusion of information. Daily analyses can provide managers with an early warning of harm and an early prescription for a remedy.

Finally, the study examines halo (or spillover) effects related to automobile recalls at the nameplate (i.e., automobile model) level across 48 nameplates. Analyses at the nameplate level provide more depth, less bias, and more insight than aggregate analyses.

In particular, the current study seeks to answer the following questions:

- Does perverse halo exist in online chatter? That is, does negative online chatter about one nameplate spill over into negative online chatter about another nameplate?
- What are the patterns of perverse halo across nameplates within and between brands?
- Is perverse halo affected by a brand's market share and country of origin?
- How quickly do these effects take to wear in and wear out? That is, what are the dynamics of the effect?
- What is the effect of apology advertising about recalls on the online chatter about the recalled nameplate and its rivals?
- What are the effects of perverse halo on downstream sales and stock market performance?

To address these questions, we assemble a data set of online chatter for 48 nameplates across four car brands, three Japanese and one American, during a series of product recalls. Automobiles are a relevant category in which to test the phenomenon because they have recently witnessed approximately 157 million recalls in the past six years, representing a 61% increase over the recalls in the prior six years (Andrews and Aisch 2014). We use a range of metrics and econometric models to ensure that the results are robust. In our disaggregate analysis, we assemble data at a daily level for a period of 470 days. We evaluate whether negative online chatter about one nameplate increases the negative chatter about another nameplate. Next, we run two types of aggregate analysis. We analyze the effect of negative chatter on stock market performance (daily) at the brand level and on sales (monthly) at the nameplate level. We aggregate the chatter about the nameplates to the brand level for analyzing the effect of negative chatter about the recalled brand on a rival brand's abnormal stock returns. We aggregate the negative chatter to the monthly level for analyzing the effect of the chatter about the recalled nameplate on another nameplate's sales. Moreover, we also evaluate the role of apology advertising about product recalls in influencing the negative online chatter about the recalled nameplate and its rivals.

Relative to the literature, we find that negative chatter about product recalls of a focal brand can increase negative chatter about rival brands. We call this phenomenon perverse halo. Perverse halo depends on the similarity between the focal and rival brand's market shares and countries of origin. It is stronger for brands that are from the same country and have similar market shares. Moreover, we find that the negative chatter about a focal brand can have damaging effects on the sales and stock market performance of rivals.

The rest of the article is organized as follows. The second section presents the theory, the third section explains the method, the fourth section describes the model, and the last two sections present the results and discussion.

THEORY

Definitions

We define the key terms relevant to the study: brand, subbrand, nameplate, and perverse halo. There are three levels of branding in the automobile industry. The term "brand" refers to the manufacturer that makes the automobiles (e.g., Toyota Motor Corporation). "Subbrand" refers to automobiles with their own name and visual identity that are under the manufacturer brand (e.g., Toyota, Lexus), and "nameplate" is the name of the automobile model under the subbrand (e.g., Corolla or Camry for certain Toyota nameplates). We define "perverse halo" as the phenomenon whereby negative chatter about one nameplate spills over into negative chatter for another nameplate.

Why Does Perverse Halo Occur?

The accessibility–diagnosticity theory proposed by Feldman and Lynch (1988) suggests that if a consumer thinks nameplate A is diagnostic of (i.e., informative about) nameplate B, the consumer will use perceptions of nameplate A's quality to infer quality of nameplate B. However, this inference occurs only when both nameplates and their quality perceptions are accessible (i.e., retrievable from memory) at the same time. Thus, the possibility of perverse halo depends on the existence and strength of association between nameplates in a consumer's memory.

[1] See http://blog.evolve24.com/food-recalls-year-ever-4-key-learnings-recalls/; https://www.facebook.com/frisco.moms/posts/787703921251086.

[2] See http://www.cpsc.gov/en/Business–Manufacturing/Recall-Guidance/Social-Media-Guide-for-Recalling-Companies/.

Associative network theory posits that consumers have networks wherein information about products and their attributes reside in the consumer's knowledge network as interconnected nodes (Collins and Loftus 1975; Janakiraman, Sismeiro, and Dutta 2009). Nameplates are interconnected in the consumer's mind through linkages between such nodes. The accessibility of nameplate A when nameplate B is mentioned increases with increasing linkage strength between the two nameplates.

We posit that perverse halo occurs when two nameplates are similar. High similarity leads to an increase in both accessibility and diagnosticity (Janakiraman, Sismeiro, and Dutta 2009). Some factors that can increase the perception of similarity between nameplates are common ownership and similar attributes such as size, country of origin, and production processes.

Perverse halo is initiated by the announcement of the recall. The announcement of the recall can be voluntary, whereby the firm recalls without any external persuasion, or it can be involuntary, whereby the firm is pressured by the NHTSA to recall. Consumers learn about the recall directly from sources such as the firm, NHTSA, and news media if they miss the firm or NHTSA announcement. Prior research has found that recalls damage the firm's reputation in consumers' minds (Dawar 1998; Dawar and Pillutla 2000). Such damage leads consumers to post negative chatter about the recalled nameplate in message boards, forums, blogs, and review sites. Indeed, consumer use of social media is pervasive and mobile. Nowadays, nearly four in five active Internet users engage in social media (Nielsen 2011). Negative chatter about the recalled nameplate then affects negative chatter about other nameplates of the same brand and of different brands.

After the recall is announced, online chatter about the recalled nameplate appears to the consumers as "negative news" spread over days. Indeed, consumers educate themselves about nameplates, brands, products, and services through online chatter that inform their purchase and loyalty behavior (Blackshaw and Nazzaro 2006).

We posit that after the recall announcement, consumers react by posting negative chatter about the recalled nameplate. Topics of such negative chatter could range from the faulty attribute ("safety") to the overall quality of the nameplate. In fact, such chatter can provide scoops and insights that the recall announcement missed. For example, an affected consumer might indicate a reason for the vehicle fault. Subsequently, unaware consumers, who have missed the announcement of the recall, might read the negative chatter and infer that another nameplate of the same brand or of a different brand could have similar problems. Alternatively, unaffected consumers who at first do not infer negative quality of a similar nameplate might, over time, change their minds. This reasoning suggests the following hypothesis:

> H_1: Perverse halo exists in online chatter.

Does Perverse Halo Depend on the Country of Origin?

Several factors can increase perceptions of similarity between nameplates, leading to perverse halo. One factor is the country of origin of the nameplates. Research on country of origin effects has suggested that country perceptions can moderate perverse halo (Maheswaran and Chen 2006). Prior research has suggested that consumers might use "country" as an attribute and make similar inferences for nameplates that belong to the same country as the recalled nameplate and opposing inferences for nameplates that belong to a different country (Hong and Wyer 1989, 1990). For example, consumers might think that nameplates from the same country have similar processes of product development. Indeed, in many cases, nameplates of different brands use the same source and production processes to develop products (Hora, Bapuji, and Roth 2011; Kraljic 1983).

Maheswaran (1994) finds that both experts and novices use country of origin in product evaluations when there is ambiguity in attribute information. Indeed, high ambiguity exists in determining the root cause of automobile recalls. For example, the Toyota acceleration crises exemplified this ambiguity because there was lingering doubt about the cause of the sudden accelerations.[3] Moreover, Maheswaran and Chen (2006) find that country of origin effects occur more when consumers are angry. Anger among consumers tends to be common in automobile recalls (Choi and Lin 2009).[4] This reasoning suggests the following hypothesis:

> H_2: Perverse halo effects are stronger between brands from the same country.

Does Perverse Halo Depend on a Brand's Dominance?

We define brand dominance in terms of the brand's market share: a higher share indicates greater dominance. Perceptions of similarity between a nameplate and a rival nameplate can be asymmetric, which leads to asymmetric perverse halo effects. For example, a product recall of nameplate A might not influence evaluations of nameplate B to the same extent that the same recall for nameplate B would influence evaluations of nameplate A. Indeed, associative network theory posits that linkages between two nameplates can point in both directions and that there can be asymmetry in the strength of brand associations from one direction to the other (e.g., Collins and Loftus 1975). Thus, this asymmetric strength of association suggests asymmetric vulnerability of nameplates.

We posit that perverse halo will be stronger from a dominant brand to a less dominant brand than vice versa. That is, downward perverse halo is stronger than upward perverse halo. We suggest several reasons for this asymmetry. Categorization theory suggests one factor: typicality of the brand within a product category (Barsalou 1992; Smith and Medin 1981). Typicality is the brand-to-category associative strength, whereby a brand name activates various features that categorize the focal category (Farquhar, Herr, and Fazio 1990). Prior research has suggested that a brand scandal is more likely to spill over to other brands in the same category if the focal brand is a typical rather than an atypical member of the category (Roehm and Tybout 2006). Dominant brands are perceived by consumers to be more typical of a category (Loken and Ward 1990, p. 112). Thus, perverse halo is more likely to occur from nameplates of more dominant brands to nameplates of less dominant brands. This line of reasoning suggests the following hypothesis:

> H_3: Perverse halo effects are stronger from a dominant brand to a less dominant brand (downward) than vice versa (upward).

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[3]See http://www.safetyresearch.net/Library/ToyotaSUA020510FINAL.pdf.

[4]See http://www.cbsnews.com/news/toyota-recall-fuels-confusion-anger/.

METHOD

Research Design

Industry context. We select the U.S. automobile industry to analyze the effect of recalls for several reasons. First, this industry has a high frequency of recalls, which provides an ample number of recall events for our analysis. Between 1966[5] and 2014, firms and the NHTSA recalled more than 588 million vehicles (Andrews and Aisch 2014). Yearly recall rate has increased since 1990, peaking in 2014 (63 million vehicles). Reasons for this increase, among others, include complexity of cars, changes in the regulatory environment, and common sourcing (Bae and Benítez-Silva 2012; Peters 2005).

Second, the automobile industry provides a considerable amount of daily online chatter as consumers actively and frequently participate in numerous social media sites dedicated to the auto industry. The high-involvement nature of the automobile category leads consumers to discuss and gather information related to nameplates. Most other industries with frequent recalls do not have as rich a data source at the daily level with which to work. Such disaggregate temporal analysis is essential to get deep insights into dynamics and avoid biased estimates (Tellis and Franses 2006).

Third, offline advertising for nameplates, such as television advertising and media citations, is available and varies at the daily level. Having data on variation in advertising expenditure and media citations at the daily level is necessary to synchronize with online chatter at the daily level.

Finally, the automobile industry is of considerable economic significance. It represents 3% of U.S. GDP and accounts for 1 in 7 jobs in the U.S. economy (Kalaignanam, Kushwaha, and Eilert 2013; Pauwels and Srinivasan 2004).

Sampling of brands and nameplates. We selected 48 nameplates from four brands for our empirical analysis. We list the nameplates used in our analysis in Table B1 in Web Appendix B.

We use the following brands in our sample: Toyota, Honda, Nissan, and Chrysler. We selected these brands because they constitute four of the five brands that had the most recalls in 2010. Toyota led in number of recalled units, followed by General Motors, Honda, Nissan, and Chrysler (Jensen 2011). We were unable to get chatter data about General Motor's brands or nameplates, but the remaining four brands provide an ample number of recalls to test perverse halo in online chatter. In general, the market share ranking for these four brands has been fairly stable—Toyota at the top, then Honda, Nissan, and Chrysler—for many years. Even though Toyota, Honda, and Nissan have been moving manufacturing to the United States, consumers still view these brands as Japanese, because of their origin and ownership. Thus, this sampling strategy allows us to evaluate to some extent whether perverse halo is moderated by market share and country.

In our disaggregate analysis, we analyze halo at the nameplate level for several reasons. First, distinct branding takes place at the nameplate level (e.g., Camry vs. Accord). Second, it is more granular, permitting measurement of halo across 48 nameplates instead of only four brands. Third, it allows us to analyze perverse halo by segment (e.g., large pickup, small van). This allows us to tease out idiosyncratic segment effects and selection bias due to brand participation. Finally, it allows us to test against the condition of no recalls because some nameplates did not have any product recalls.

Time frame. We focus on the period from January 1, 2009, to April 15, 2010, because this period witnessed a high number of recalls and because we could obtain online chatter data only through April 15, 2010. In 2010 alone, more than 20 million vehicles were recalled.

Design. We select both voluntary and involuntary recalls in our empirical analysis, and we exploit the large number, high variability, and apparent randomness of the recalls. We acknowledge that it is possible recalls could be endogenously determined by consumer reaction in online chatter, and thus our design is not a rigorous experiment. However, we test the assumption of recalls as a random shock in our empirical tests. We run the typical time series checks, such as testing for serial correlation, trends, seasonality, and stationarity. We find no evidence of temporal causality from negative online chatter to recalls; that is, negative online chatter does not Granger-cause recalls (Granger 1969).

We assume that a recall shock leads to a big increase in negative online chatter about the recalled nameplate. But in the absence of perverse halo (the null hypothesis), recalls should not affect negative online chatter about other nameplates. We track chatter before, during, and after each recall for recalled nameplates as well as other nameplates that had no recalls. Thus, the effect of recalls on chatter allows for a quasi-experimental manipulation, and our design constitutes a repeated natural event or quasi-experiment.

Data Collection of Online Chatter

We obtained the online chatter data from a third-party data provider. The firm uses its proprietary software to mine and content-code the chatter using techniques such as natural language processing, machine learning, text mining, and statistical analysis. The online chatter span postings about the four brands and 48 nameplates on various platforms of social media. The online chatter is sourced from forums such as Automotiveforums.com, blogs such as Thetruthaboutcars.com, and review sites such as Edmunds.com. Overall, approximately 1,000 sites were sourced to obtain the data. In the original data provided to us, nameplates were not mentioned. Thus, we visited each specific blog, review, and forum and determined the nameplate discussed in order to link the chatter to the nameplate level. This effort took approximately 250 man-hours.

The third-party data provider scraped these sites to obtain any chatter across these social media platforms that mentioned the focal nameplates across the time frame of our study. The firm then used its proprietary algorithm that quantifies the content of the chatter by generating tag data (similar to coding) on three dimensions at the sentence level: subject, attribute, and valence. For example, for online chatter with a sentence such as, "One cannot be safe in a Corolla," the subject is Corolla, the attribute is safety, and the valence is negative. The algorithm also considers other inherent attributes of online chatter in its classification such as the URL, author information, post time, and so on. Moreover, to improve accuracy, the algorithm goes beyond

[5]The recall system was introduced in the United States in 1966 through the National Traffic and Motor Vehicle Safety Act. This was done to remove potentially dangerous vehicles from the road and resolve safety issues.

keyword-based technology, which simply decomposes chatter into a list of words without any stemming (e.g., “love,” “loved,” and “loving” appear as separate words instead of being stemmed to “love”) or any consideration of their meaning (e.g., all instances of the word “stock” are treated the same way, even though the word can mean “company share,” “stored goods,” or “broth”). The details of the third party’s classification algorithm appear in Web Appendix C.

We independently checked the accuracy of the algorithm’s classification with the help of two research assistants. For this purpose, we randomly selected 500 samples of online chatter from the total corpus of negative online chatter. Two research assistants independently read each post in the chatter and classified the chatter as positive, negative, or neutral. The interrater agreement was 86%. We found the algorithm to have a classification accuracy of 80%; that is, 80% of the chatter classified as negative by the algorithm was also classified as negative by both research assistants.

Measures of Endogenous Variables

Measures of online chatter. We use negative online chatter about the nameplate’s recall attribute (i.e., negative chatter that mentions product recall) as the measure of online chatter for all nameplates that belong to the three Japanese brands (Toyota, Honda, and Nissan). We use negative online chatter about publicized problems with a nameplate’s acceleration as the online chatter metric for the six nameplates belonging to the American brand (Chrysler). We use negative chatter about the acceleration attribute and not the recall attribute for Chrysler’s nameplates because negative chatter about recall was not collected by the third-party data provider for Chrysler’s nameplates. We use the term “concerns” to mean negative chatter about either the recall or the acceleration attribute.

Measures of media citations. We measure media citations about recalls or acceleration as the number of articles in print media per day that cover the nameplate’s recall or acceleration. We use media citations about recalls for the vector autoregressive models with exogenous variables (VARX) that compare the Japanese brands and media citations about acceleration for the VARX models that compare Toyota and Chrysler. We used LexisNexis to search all U.S. newspapers and newswires for any article that mentions the nameplate and its recall or acceleration. We used LexisNexis’s relevancy score feature to ensure that we selected only relevant articles and not chance mentions. We identified an article as relevant if LexisNexis gave it a relevancy score of 60% or higher. We used 60% as the threshold because prior research has used it (Tirunillai and Tellis 2012) and because a higher threshold (e.g., 70%) might cause us to miss articles that are related to product recall or acceleration.

We use media citations as an endogenous variable in our model because the agenda setting theory argues that consumers regard an issue as important according to the saliency (i.e., the rate and prominence of coverage) of the issue in the media (McCombs and Shaw 1972). Moreover, it is possible that journalists read about the nameplate’s recall in blogs, forums, and review sites, which in turn inform their journalistic pieces. Thus, online chatter about a recalled nameplate can trigger media citations about that nameplate and other nameplates.

ABC news coverage. Our sample period includes the crisis over Toyota cars’ spontaneous acceleration, which was first broken by ABC News and heavily covered by that network (Ross et al. 2009). We control for this coverage and measure ABC news coverage of the acceleration crisis by counting the number of times Toyota’s recall was mentioned in ABC news programs. We used the LexisNexis database to obtain the ABC transcripts and text-mine the transcripts to find keywords related to Toyota’s acceleration. We include ABC news coverage as an endogenous variable because the explosion of the crisis among consumers in social media may have spurred further news coverage by ABC.

Negative events in Toyota’s acceleration crisis. We measure negative events related to Toyota’s acceleration crisis by an indicator variable (on any given day, 1 = negative event; 0 = no negative event). We examine content related to the crisis in the LexisNexis and Factiva databases and use the Greto, Schotter, and Teagarden (2010) case to identify the dates of negative events. These data are listed in Web Appendix D. We use these events as an endogenous variable because they might have stimulated concerns for both Toyota’s nameplates and nameplates from other brands. Conversely, negative events could have been spurred by the online chatter about Toyota.

Advertising. We measure a nameplate’s advertising by the daily dollar spend for advertising the nameplate in television stations in the United States. We obtained the advertising data from the Kantar Stradegy database. We deflated the advertising spend by the monthly consumer price index. Then, we classified advertising by content into four types, using Kantar Stradegy’s categorization scheme: general, promotional, leasing, and advertisements that were part of Toyota’s campaign in which the firm apologized for its acceleration crisis. Note that Toyota’s apology advertisements were not for a specific nameplate.

We use advertising as an endogenous variable because nameplates may advertise in response to an increase in concerns. However, prior research has found a decrease in recalled brands’ own advertising elasticities (Van Heerde, Helsen, and Dekimpe 2007). Indeed, brands often increase their advertising in the wake of a competing brand’s misfortune (Cleeren, Dekimpe, and Helsen 2008). Rivals see recalls as an opportunity to win over consumers from the recalled brand.

Key developments. We measure key developments, which include a brand’s press releases, by counting the number of times a brand underwent a key development, such as earnings announcements, acquisitions, strategic alliances, awards, and so on. We use key developments as an endogenous variable because these developments can affect online chatter and in turn lead brands to engage in another key development. We obtain the key developments data from brands’ websites and the S&P Capital IQ database.

Measures of Exogenous Variables

Recalls. We use the total number of recalled units in each recall as the measure for recalls. We used the Office of Defects Investigation’s database of recalls to identify the dates, nameplates, brands, and units involved in each recall. This database captures all recalls, voluntary or involuntary.

The database covers all vehicle and equipment recalls for which the brand has official responsibility.[6] We do not have data on the severity of recalls because that information is no longer provided by the NHTSA.[7] We matched the recalled nameplates with each of the four brands (e.g., Toyota Corolla sedan matched with Toyota Motor Corporation). To confirm the details and dates of the recalls, we consulted automobile sites (e.g., www.cars.com, www.autoblog.com) and teaching cases (e.g., Greto, Schotter, and Teagarden 2010; Quelch, Knoop, and Johnson 2010). Web Appendix E lists the recalls. We use recalls as an exogenous variable because the recall event for any one of the nameplates of a brand leads to an increase in negative chatter about the recalled nameplate and other nameplates. We ran Granger causality tests to check whether the recalls variable was endogenous. We ran the tests until 20 lags and did not find substantial evidence that would indicate Granger causality for recalls (Granger 1969).

New product introductions. We measure new product introductions by counting the number of times a brand introduced a new product. We used brands' websites and the Capital IQ database to collect the data. We use new product announcements as an exogenous variable because it may increase overall chatter or reduce concerns due to consumers' enthusiasm about new cars. We did not find evidence that would indicate that negative online chatter Granger-caused new product introductions (Granger 1969).

STATISTICAL MODELING

This section first explains why we use the VARX approach to estimate the relationship among concerns of the various nameplates and then explains the VARX equation (Dekimpe and Hanssens 1995). Because the VARX framework has been used in prior research, we explain the steps in Web Appendix F.

Why the VARX Framework?

We use the VARX framework for three reasons. First, it allows estimation of Granger causality among a set of variables (endogenous variables) through use of their lagged values. Second, it ensures robustness of the model to issues of nonstationarity, spurious causality, endogeneity, serial correlation, and reverse causality (Granger and Newbold 1986). Third, it permits estimation of the long-term or cumulative effects of causal variables using the impulse response functions (Nijs, Srinivasan, and Pauwels 2007; Tirunillai and Tellis 2012).

VARX Framework

We estimate the relationships between concerns and other endogenous variables of the various nameplates using the VARX framework. For ease of exposition, below is the specification using levels of the variables for the Japanese nameplates belonging to the Small Pickup segment (see Table A1 in Web Appendix A).

(1)

$$
\begin{bmatrix} \mathrm{ConTac}_t \\ \mathrm{ConRid}_t \\ \mathrm{ConFrt}_t \\ \mathrm{MedTac}_t \\ \mathrm{MedRid}_t \\ \mathrm{MedFrt}_t \\ \mathrm{AdTac}_t \\ \mathrm{AdRid}_t \\ \mathrm{AdFrt}_t \\ \mathrm{ABCToy}_t \\ \mathrm{NegToy}_t \\ \mathrm{KDToy}_t \\ \mathrm{KDHon}_t \\ \mathrm{KDNis}_t \end{bmatrix}
=
\begin{bmatrix} \alpha_{\mathrm{ConTac}} + \delta_{\mathrm{ConTac}} \times t \\ \alpha_{\mathrm{ConRid}} + \delta_{\mathrm{ConRid}} \times t \\ \alpha_{\mathrm{ConFrt}} + \delta_{\mathrm{ConFrt}} \times t \\ \alpha_{\mathrm{MedTac}} + \delta_{\mathrm{MedTac}} \times t \\ \alpha_{\mathrm{MedRid}} + \delta_{\mathrm{MedRid}} \times t \\ \alpha_{\mathrm{MedFrt}} + \delta_{\mathrm{MedFrt}} \times t \\ \alpha_{\mathrm{AdTac}} + \delta_{\mathrm{AdTac}} \times t \\ \alpha_{\mathrm{AdRid}} + \delta_{\mathrm{AdRid}} \times t \\ \alpha_{\mathrm{AdFrt}} + \delta_{\mathrm{AdFrt}} \times t \\ \alpha_{\mathrm{ABCToy}} + \delta_{\mathrm{ABCToy}} \times t \\ \alpha_{\mathrm{NegToy}} + \delta_{\mathrm{NegToy}} \times t \\ \alpha_{\mathrm{KDToy}} + \delta_{\mathrm{KDToy}} \times t \\ \alpha_{\mathrm{KDHon}} + \delta_{\mathrm{KDHon}} \times t \\ \alpha_{\mathrm{KDNis}} + \delta_{\mathrm{KDNis}} \times t \end{bmatrix}
+ \sum_{l=1}^{L}
\begin{bmatrix} \beta^l_{1,1}, \ldots, \beta^l_{1,14} \\ \beta^l_{2,1}, \ldots, \beta^l_{2,14} \\ \ldots \\ \ldots \\ \beta^l_{13,1}, \ldots, \beta^l_{13,14} \\ \beta^l_{14,1}, \ldots, \beta^l_{14,14} \end{bmatrix}
\begin{bmatrix} \mathrm{ConTac}_{t-1} \\ \mathrm{ConRid}_{t-1} \\ \mathrm{ConFrt}_{t-1} \\ \mathrm{MedTac}_{t-1} \\ \mathrm{MedRid}_{t-1} \\ \mathrm{MedFrt}_{t-1} \\ \mathrm{AdTac}_{t-1} \\ \mathrm{AdRid}_{t-1} \\ \mathrm{AdFrt}_{t-1} \\ \mathrm{ABCToy}_{t-1} \\ \mathrm{NegToy}_{t-1} \\ \mathrm{KDToy}_{t-1} \\ \mathrm{KDHon}_{t-1} \\ \mathrm{KDNis}_{t-1} \end{bmatrix}
+ \begin{bmatrix} \gamma_{1,1} & \cdots & \gamma_{1,p} \\ \vdots & \ddots & \vdots \\ \gamma_{p,1} & \cdots & \gamma_{p,p} \end{bmatrix}
\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{bmatrix}
+ \begin{bmatrix} \varepsilon_{\mathrm{ConTac},t} \\ \varepsilon_{\mathrm{ConRid},t} \\ \varepsilon_{\mathrm{ConFrt},t} \\ \varepsilon_{\mathrm{MedTac},t} \\ \varepsilon_{\mathrm{MedRid},t} \\ \varepsilon_{\mathrm{MedFrt},t} \\ \varepsilon_{\mathrm{AdTac},t} \\ \varepsilon_{\mathrm{AdRid},t} \\ \varepsilon_{\mathrm{AdFrt},t} \\ \varepsilon_{\mathrm{ABCToy},t} \\ \varepsilon_{\mathrm{NegToy},t} \\ \varepsilon_{\mathrm{KDToy},t} \\ \varepsilon_{\mathrm{KDHon},t} \\ \varepsilon_{\mathrm{KDNis},t} \end{bmatrix}.
$$

Here ConTac, ConRid, and ConFrt denote concerns for Tacoma, Ridgeline, and Frontier nameplates, respectively. MediaTac, MediaRid, and MediaFrt denote media citations about recall for Tacoma, Ridgeline, and Frontier respectively. AdTac, AdRid, and AdFrt denote general advertising for

[6]We also estimate VARX equations for cases in which an outside manufacturer claimed responsibility for faulty equipment used in any one of the 48 car nameplates in our sample, and find similar results. For example, Sabersport recalled 16,270 lamp assemblies used in some Toyota nameplates.

[7]The severity or hazard level of the recall encompassed four levels. This score was provided by NHTSA until 2001, when the organization stopped providing this information.

Tacoma, Ridgeline, and Frontier, respectively. (Note that for ease of exposition, we have not included the endogenous variables for promotional and leasing ads for each nameplate or Toyota's apology advertisements in Equation 1. This would add seven more endogenous variables, thereby increasing the number of endogenous variables to 21.) ABCToy denotes ABC news coverage on the Toyota acceleration crisis, NegToy denotes negative events in Toyota's acceleration crisis, and KDToy, KDHon, and KDNis denote key developments for Toyota, Honda, and Nissan, respectively. The set $x_1, ..., x_p$ comprises the p control variables. Along with recalls and new product announcements, we add three additional controls: (1) day of the week dummies to control for weekday and weekend effects; (2) holiday dummies (Halloween, Thanksgiving, Christmas, New Year's Day, Martin Luther King Day, Labor Day, Memorial Day, etc.) to control for holiday and seasonal effects, in which consumers may be less receptive to news about recall events during holidays; and (3) a deterministic time-trend variable, which captures the effect of omitted, gradually changing variables. The variables $\alpha, \delta, \beta,$ and γ are the parameters to be estimated, and ε_t are white noise residuals, which are distributed as $N(0, \Sigma)$.

The coefficients $\beta_{1,2}$ and $\beta_{1,3}$ estimate the effect of perverse halo of online chatter about Ridgeline and Frontier, respectively, on Tacoma. The coefficients $\beta_{2,1}$ and $\beta_{2,3}$ estimate the effect of perverse halo of online chatter about Tacoma and Frontier, respectively, on Ridgeline. The coefficients $\beta_{3,1}$ and $\beta_{3,2}$ estimate the effect of perverse halo of online chatter about Tacoma and Ridgeline, respectively, on Frontier. On the basis of the augmented Dickey–Fuller, Phillips–Perron, and cointegration tests, we chose the proper appropriate specification for the endogenous variables that enter the VARX equation.

RESULTS

This section presents the descriptive results of the disaggregate analysis, which include the tests and estimates of the VARX framework and estimates of halo. Note that all analysis here is at the nameplate level. However, for purposes of summarization and ease of presentation, we then aggregate these estimates to the brand level. Next, we present the results of the aggregate analysis, which include the effects on sales and stock market performance.

Descriptive Results

Figure 1 shows the pattern of recalls and concerns during the time frame of the study for all nameplates of the Japanese automobile brands. The solid arrows below the horizontal axis show recalls and other events related to Toyota's recall (e.g., ABC news investigation report on Nov. 3). The arrow sizes suggest the size of each recall in terms of number of units recalled. Not all recalls are shown because of space limitations. Concerns (i.e., amount of negative chatter) seem to correlate with recalls. There are spikes in Toyota's concerns corresponding to its large recalls. Similarly, there are spikes in Honda's concerns corresponding to its large recalls. Note the steep rise in the number of concerns for Toyota after January 21, 2010. It takes approximately two months for the concerns to die down and return to their previous level. There are minor spikes in the number of concerns for Honda during that week. Other recall events shown on the graph correspond to increases in not only the recalled brand's concerns but also a rival's concerns. For example, Honda's recall on March 16 increases concerns for both Honda and Toyota.

Note that there is considerable variation in the timing and size of recalls, which allows a rich analysis of variance. Due to concomitant other effects (e.g., media citations, advertising), it is difficult to determine statistical effects or temporal causality merely from these graphical associations. The VARX framework will enable us to rigorously test whether such associations are causal in the sense of Granger causality. We identify the effects of one nameplate's recall on another nameplate by (1) exploiting the separation of the recall dates across nameplates, (2) using the variation in the number of units recalled for each nameplate, and (3) including several nameplates from the four brands (Toyota, Honda, Nissan, and Chrysler) that had no product recalls in the sample time frame. In case of an overlap of recall dates, the variation in recalled units between the two nameplates enables us to estimate the effects. Web Appendix G contains the descriptive results (means and standard deviations) of the endogenous variables across the VARX equations.

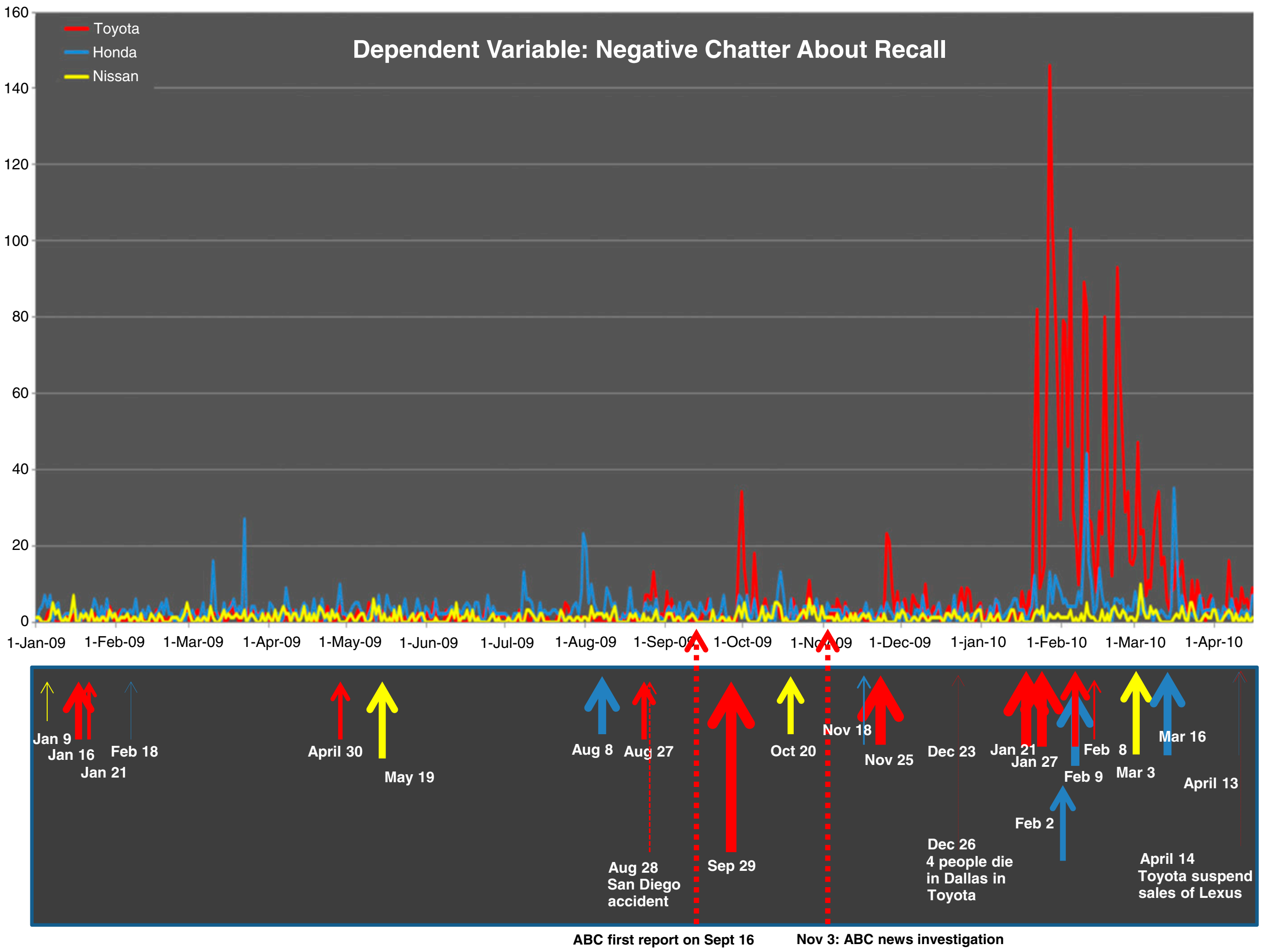
Estimates of VARX Framework

The results of tests for stationarity, cointegration, and structural break are in Web Appendix H. The optimal lag length is 1 for most of the 17 VARX equations, except in a few cases in which it is 2, as per the (Schwartz's) Bayesian information criterion. Our results are not affected by the presence of any residual correlation, nonnormality of residuals, or heteroskedasticity. We estimate the VARX models using an ordinary least squares regression, accounting for heteroskedasticity and potential serial correlation with the Newey–West estimator (Newey and West 1987). The average parameter-to-observation ratio for each equation across the 17 VARX models is 1:16.6. We report the number of parameters and degrees of freedom in Web Appendix I. Note that because each equation contains exactly the same set of regressors, the ordinary least squares estimates are numerically identical to seemingly unrelated regression estimates (Zellner 1962). Using these estimates, we then compute the effect of one variable on another over time, taking current and carryover effects, using the generalized impulse response function (GIRF), explained in Web Appendix F. In our robustness tests, in the interests of parsimony in specification and efficiency in estimation, we drop variables from the VARX model that do not significantly affect the dependent variables (across each equation) at least 25% of the time. We then re-estimate the VARX model using only the "important" variables. The results of this procedure are available in Web Appendix J. Our findings remain the same when we use this method.

Estimation of Halo

We use the estimates of the GIRF from the VARX equations to calculate the amount of overlap of perverse halo among the three Japanese brands and between Toyota and Chrysler. To explain the meaning of these estimates, Table 1 provides a simple case of two nameplates (A and B) and two endogenous variables (concerns and media citations about recall). In this example, the key off-diagonal

Figure 1
GRAPH OF RECALLS AND CONCERNS FOR TOYOTA, HONDA, AND NISSAN



Notes: The solid arrows below the x-axis indicate recall dates. Arrow size corresponds to the size of the recall. The dotted arrows indicate dates of important news related to the recalls. The colors indicate the different brands: red = Toyota, blue = Honda, yellow = Nissan.

elements (cross-nameplate effects in boldface) in the first two columns provide estimates of perverse halo because they capture the effect of concerns about one nameplate (independent, or causal, variable) on concerns about the other nameplate (dependent or, effect, variable).[8]

Estimates of halo among brands by segment. We first examine perverse halo between nameplates of different brands. Recall that the GIRF tracks the impact over time of a unit shock (one standard deviation) to one independent variable on a dependent variable. Because the number of nameplates is large (48), a single VARX equation to estimate all cross-nameplate effects would result in 2,256 GIRF estimates ($nP2 = 48 \times 47 = 2,256$). It would be extremely complex to keep track of and interpret all these cross-nameplate effects. In the interests of parsimony and ease of presentation, we first estimate GIRF cross-nameplate effects by segment of nameplates. In addition, estimating the GIRF effects by segment allows us to tease out idiosyncratic segment effects and selection bias due to brand participation.

For the three Japanese brands, we use 12 segments according to the definition of nameplate segmentation in *Ward's Automotive Yearbook* (WardsAuto 2010/2011; see Table A2 in Web Appendix A). *Ward's* divides cars into different segments according to length of the vehicle and price range. Prior research has used the *Ward's* classification scheme by segment (Olivares and Cachon 2009). Note that we analyze the data for the three Japanese brands and Toyota/Chrysler separately because there is a

[8]The VARX equation also provides estimate of carry-over (effects of past values of a variable on its current value for the same car nameplate), direct effects (effects of past media citations on current concerns for the same car nameplate), feedback (effects of past concerns on current media citations for the same car nameplate) and reaction (effects of past media citations about one car nameplate on current media citations about another car nameplate). In the interest of parsimony, we do not discuss these types of estimates; that is, our focus is on perverse halo estimated by coefficients when concerns are both the cause and the effect variable.

Table 1

INTERPRETATION OF GIRF COEFFICIENTS FOR THE CASE OF TWO NAMEPLATES, A AND B, AND TWO VARIABLES, CONCERNS AND MEDIA CITATIONS ABOUT RECALLS

	Effect			
	Concerns		*Media Citations About Recalls*	
Cause	*Nameplate A*	*Nameplate B*	*Nameplate A*	*Nameplate B*
Nameplate A concerns	Carryover	**Halo A→B**	Feedback: Direct A→A	Feedback: React A→B
Nameplate B concerns	**Halo B→A**	Carryover	Feedback: React B→A	Feedback: Direct B→B
Nameplate A media citations about recalls	Direct A→A	**Halo A→B**	Carryover	React A→B
Nameplate B media citations about recalls	**Halo B→A**	Direct B→B	React B→A	Carryover

Notes: "Direct" means the effect of variable X_1 for brand A on variable X_2 for brand A; "React" means the effect of variable X_1 for brand A on variable X_2 for brand B. Arrows indicate the direction of the effect from cause to effect. The hypothesized effect of perverse halo is indicated by boldfaced type.

discrepancy in the attributes of online chatter between these two groups of brands.[9] Thus, we estimate 12 VARX equations, one for each segment of nameplates belonging to the Japanese brands. Similarly, Table A3 in Web Appendix A shows the five segments into which *Ward's* classifies the Toyota and Chrysler nameplates. Here, we estimate five VARX equations, one for each segment of nameplates belonging to Toyota and Chrysler. Web Appendix I reports the cumulative GIRF for these 17 VARX equations.

Computation of halo among brands by segment. The computation of halo is based only on the sign and significance of cross-nameplate GIRF estimates, between any two nameplates. Consistent with the vector autoregression literature (Pauwels, Hanssens, and Siddarth 2002; Pauwels and Srinivasan 2004; Sims and Zha 1999; Trusov, Bucklin, and Pauwels 2009), we follow established practice in marketing research and assess the statistical significance of each impulse response value by applying a one-standard-error band to evaluate whether each generalized impulse response value is significantly different from 0. We also use different significance levels, and our substantial results remain the same. To provide a measure of perverse halo, we compute the extent of perverse halo between brands within a segment as the percentage of times that concerns about any nameplate of one brand have a significant positive effect on concerns about any nameplate of another brand. A value of 0% would imply no perverse halo, suggesting that the two brands were completely distinct in consumers' perceptions. A value of 100% would imply perfect perverse halo, suggesting the two brands were indistinguishable in consumers' perceptions. Any value between these two would signify the extent to which negative concerns about one brand perversely affect the other brand. Note that all this is based on the cross-nameplate GIRF estimates within segments.

We define the extent of one-way perverse halo from brand A to brand B, according to the nameplates of these brands, as follows:

$$(2)\qquad H_{A\to B} = \frac{\left\{\sum_{(q=1\text{ to }Q)}\sum_{(p=1\text{ to }P)}E_{(Ap\to Bq)}\right\}}{(P\times Q)},$$

where $E_{(Ap\to Bq)}$ takes the value 1 if the GIRF estimate in the VARX equation running from the pth nameplate of brand A to the qth nameplate of brand B is significantly positive and 0 otherwise. The symmetric two-way perverse halo between brand A and brand B is the simple average of one- way perverse halos from A to B and from B to A.

We define the extent of the one-way perverse halo from brand A to both brand B and brand C, according to the nameplates of these brands, as follows:

$$(3)\qquad H_{A\to B\to C} = \frac{\left\{\sum_{(q=1\text{ to }Q)}\sum_{(p=1\text{ to }P)}E_{(Ap\to Bq)}\right\}}{(P\times Q)} \times \frac{\left\{\sum_{(r=1\text{ to }R)}\sum_{(p=1\text{ to }P)}E_{(Ap\to Cr)}\right\}}{(P\times R)}.$$

The total symmetric three-way perverse halo among brand A, brand B, and brand C is the simple average of $H_{A\to B\to C}$, $H_{B\to C\to A}$, and $H_{C\to A\to B}$.

Thus, the formula for the total symmetric two-way perverse halo, excluding the total symmetric three-way perverse halo (using Toyota as the focal case), is as follows:

$$\begin{aligned}(4)\qquad &\text{Total symmetric two-way perverse halo for Toyota}\\ &= \text{Symmetric two-way perverse halo between Toyota and Honda}\\ &\quad + \text{Symmetric two-way perverse halo between Toyota and Nissan}\\ &\quad - 2\times\text{Total symmetric three-way perverse halo}\end{aligned}$$

The exclusivity for a brand (using Toyota as the focal case) is given by the following formula:

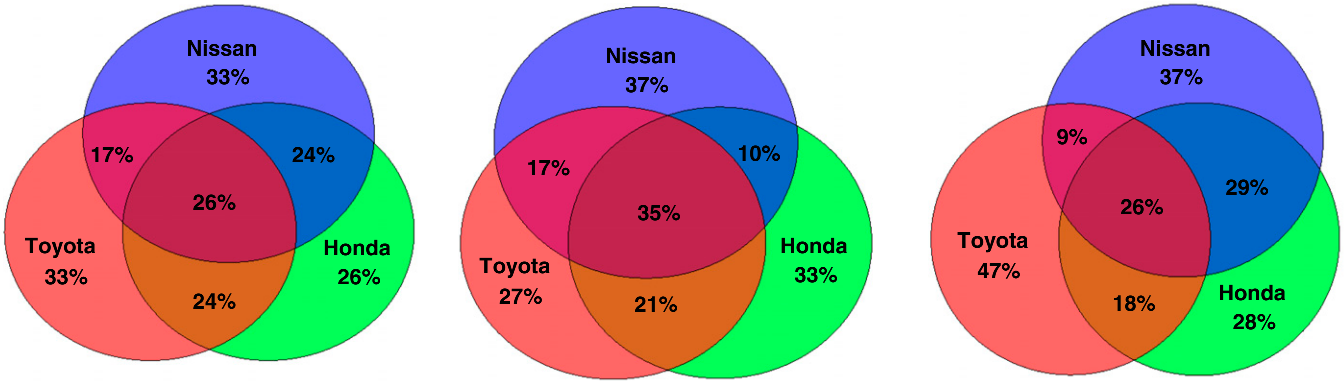
$$\begin{aligned}(5)\qquad &\text{Exclusivity}_{\text{TOYOTA}}\\ &= 100\% - (\text{Total symmetric three-way perverse halo})\\ &\quad - (\text{Total symmetric two-way perverse halo for Toyota})\end{aligned}$$

Presentation of perverse halo among brands by segment. Figure 2, Panel A, shows the estimated perverse halo among Toyota, Honda, and Nissan according to the above formulas. We find a considerable total symmetric three-way perverse halo (26%) among the three Japanese car brands. We find the highest symmetric two-way perverse halo between Toyota and Honda (50%) and Honda and Nissan (50%), followed by Toyota and Nissan (43%). Most importantly, we find that for each brand, exclusivity (i.e.,

[9]We have data on online chatter about the recall attribute for the three Japanese manufacturers and on online chatter about the acceleration attribute for Toyota and Chrysler.

Figure 2
PERVERSE HALO

A: Perverse Halo Between Japanese Brands[a]	*B: Perverse Halo from a Dominant to Less Dominant Japanese Brand*[b]	*C: Perverse Halo from a Less Dominant to a Dominant Japanese Brand*[c]



[a]The percentages in the diagram indicate the symmetric (average) perverse halo effects between two of the brands A, B, and C and among all three brands A, B, and C. These perverse halo effects are calculated using the percentage of times that concerns about any nameplate of one brand had a significant and positive effect (according to the GIRF estimates) on concerns about any nameplate of another brand.
[b]The percentages in the diagram indicate the perverse halo effects from a dominant brand A to one of two less dominant brands B and C or to both B and C (for the three-way overlap case), and from a dominant brand B to a less dominant brand C. We count cases of three-way overlap only when nameplates of Toyota affect nameplates of both Honda and Nissan.
[c]The percentages in the diagram indicate the perverse halo effects from a less dominant brand B to a dominant brand A and from a less dominant brand C to one of two more dominant brands A and B or to both A and B (for the three-way overlap case). We count cases of three-way overlap only when nameplates of Nissan affect nameplates of both Toyota and Honda.
Notes: The Venn diagrams were generated in Matlab using the Chow and Rodgers algorithm to construct area-proportional Venn diagrams (Chow and Rodgers 2005).

isolation from all perverse halo) is rather low, at only 26% for Honda and 33% for both Toyota and Nissan. Thus, perverse halo seems to be quite extensive among the three Japanese brands. Thus, we find support for H_1; that is, perverse halo exists in online chatter. Honda appears to be the least exclusive of the three brands.

There is a 36% symmetric two-way perverse halo between nameplates of Toyota and those of Chrysler. This value is lower than the two-way overlap among the three Japanese brands. The average symmetric two-way perverse halo among the Japanese car brands is 48%. This result suggests that perverse halo could be affected by consumers' perceptions of brands' country of origin. Thus, we find moderate support for H_2, which states that perverse halo is stronger for brands from the same country. In contrast, we find that negative chatter about a nameplate decreases negative chatter for another nameplate 17% of the time between Toyota and Chrysler. On average, negative chatter about one nameplate of a Japanese brand decreases negative chatter about a nameplate of another Japanese brand 12% of the time. This result again supports H_2, suggesting that perverse halo could be moderated by country of origin.

Next, we test whether perverse halo depends on a brand's dominance. According to the market shares of the brands, Toyota is the most dominant, followed by Honda and Nissan (WardsAuto 2010/2011). Prior research has shown that dominance and market share are highly correlated (Fazio 1987). Figure 2, Panel B, shows the percentage of one-way downward perverse halo, three-way downward perverse halo, and exclusivity among car nameplates of Toyota, Honda, and Nissan. The downward three-way perverse halo is the extent of one-way perverse halo from a dominant brand A to two less dominant brands B and C. A downward perverse halo occurs only when there is perverse halo from Toyota to Honda, Toyota to Nissan, or Honda to Nissan. We find a considerable three-way downward perverse halo (35%) among nameplates of the three Japanese brands. We find the most one-way downward perverse halo between Toyota and Honda (56%), followed by Toyota and Nissan (52%) and Honda and Nissan (45%).

Figure 2, Panel C, shows the percentage of one-way upward perverse halo, three-way upward perverse halo, and exclusivity among car nameplates of Toyota, Honda, and Nissan. The upward three-way perverse halo is the extent of one-way perverse halo from a less dominant brand A to two dominant brands B and C. Thus, an upward perverse halo occurs only when there is perverse halo from Honda to Toyota, Nissan to Toyota, or Nissan to Honda. We find a three-way upward perverse halo of 26% among nameplates of the three Japanese brands. Thus, the three-way overlap is higher for downward perverse halo than for upward perverse halo. We find the most one-way upward perverse halo between Nissan and Honda (55%), followed by Toyota and Honda (44%), and Toyota and Nissan (35%). The one-way perverse halo effect is stronger from Toyota to Honda than vice versa (56% vs. 44%), from Toyota to Nissan than vice versa (52% vs. 35%), and from Nissan to Honda than vice versa (55% vs. 45%). Except the last finding of the effect from Nissan to Honda being stronger than Honda to Nissan, the results support the premise that perverse halo is stronger from dominant brands to less dominant brands. Thus, we find considerable support for H_3.

We next report the average elasticity of the effects. Table 2 displays the results. We find that the elasticity of the symmetric two-way perverse halo between Toyota and Nissan is 7.1%, between Honda and Nissan is 7.0%, and between Toyota and Honda is 12.1%. These results mean a 1% increase in negative chatter about one nameplate increases negative chatter about another nameplate of the same country by approximately 8.73% (averaging the results for symmetric two-way perverse halo). We find that the symmetric two-way perverse halo between Toyota and Chrysler is 5.9%.

As for the dynamics, we find that perverse halo has a short wear-in period of one day, and most of the accumulated effect of concerns about one nameplate on concerns about another nameplate reaches the asymptote within six days. Because positive chatter can also be diagnostic of firm performance, in the robustness tests, we control for positive chatter at the brand level and include it as another endogenous variable in the VARX models. The detailed results are available in Web Appendix K. The results are similar to the main results.

Estimates of halo across nameplates within brand. We also examine perverse halo among nameplates of the same brand and find substantial within-brand perverse halo. Toyota nameplates suffer the greatest perverse halo (91%), followed by Honda (75%), Chrysler (73%), and Nissan (56%). We find that the larger the brand, the greater the overlap in perverse halo among nameplates that belong to that brand. These results suggest that perverse halo is a result of consumer awareness of the family brand (e.g., Toyota) associated with the nameplate (e.g., Camry). The details of the results are in Web Appendix L.

Effects of apology advertising about recalls. We find that on average, Toyota's apology advertisements about product recall significantly increase concerns for the two other Japanese brands 62% of the time, and these advertisements significantly increase concerns for Chrysler 40% of the time. These results suggest that consumers get primed about recalls by such advertisements. This priming leads consumers to raise concerns, more so for rival brands from the same country than for rival brands from different countries. We find that Toyota's apology advertisements about product recall significantly increase concerns for Toyota's own nameplates 71% of the time. This result suggests that brands with product recalls should decrease spending on apology advertisements during product recalls.

Table 2

ELASTICITIES OF ONLINE CHATTER

Perverse Halo	*Mean Elasticity of Chatter*
One-way perverse halo from Toyota to Nissan	13.7%**
One-way perverse halo from Nissan to Toyota	.5%
Symmetric two-way perverse halo between Toyota and Nissan	7.1%*
One-way perverse halo from Honda to Nissan	6.5%
One-way perverse halo from Nissan to Honda	7.4%*
Symmetric two-way perverse halo between Honda and Nissan	7.0%*
One-way perverse halo from Toyota to Honda	17.0%*
One-way perverse halo from Honda to Toyota	7.1%
Symmetric two-way perverse halo between Toyota and Honda	12.1%*
One-way perverse halo from Toyota to Chrysler	6.4%
One-way perverse halo from Chrysler to Toyota	5.5%
Symmetric two-way perverse halo between Toyota and Chrysler	5.9%

*$p < .05$ (two-tailed test).
**$p < .01$ (two-tailed test).
***$p < .001$ (two-tailed test).

Aggregate Analysis

Effect on rivals' sales. We test whether halo effects can affect sales of a rival's nameplates. Because it is difficult, if not impossible, to obtain sales data on nameplates at the daily or the even the weekly level, we ascertain the relationship between concerns and sales using monthly data. Thus, we aggregate the concerns and relevant endogenous variables to the monthly level. We obtained the monthly nameplates sales data from *Ward's Automotive Yearbook* (WardsAuto 2010/2011).

We have 15 months of complete data for concerns and sales data for 48 nameplates. Because of the very short time series for each nameplate, we cannot estimate a simple vector autoregressive model as before. Instead, we pool the nameplates and estimate a panel vector autoregressive (PVAR) model. Similar to our prior design, we estimate one PVAR to compare the three Japanese brands and another PVAR to compare the Toyota and Chrysler brands.

We proceeded as follows: For each nameplate of one brand, we found the nearest rival from a different brand. We consulted various automobile sources such as the *Ward's* yearbook, automobile sites such as Edmunds.com, and online reports to ascertain the pairs. The list of pairs is in Web Appendix M. We then included concerns about the nearest rival nameplate as another endogenous variable in the PVAR to test the association between a rival nameplate's concerns and the sales of a focal nameplate.

We now explain the PVAR model, which we use to estimate the relationship between concerns and sales (Holtz-Eakin, Newey, and Rosen 1988). The PVAR technique combines the traditional vector autoregressive approach, which treats all the variables in the system as endogenous, with the panel data approach, which pools across nameplates but allows for unobserved nameplate-level heterogeneity. We specify a PVAR with l lag as

$$(6) \qquad y_{it} = \mu_0 + \prod_1 y_{it-1} + \prod_2 y_{it-2} + \cdots + \prod_l y_{it-l} + \alpha_i + \lambda_t + e_{it}, i = 1, 2, 3, ..., N; t = 1, ..., T,$$

where $y_{it} = (KDF_{jt}, MEDF_{it}, GENADSF_{it}, SALESADSF_{it}, CHATF_{it}, CHATR_{rt}, SALESF_{it})$ is a seven-variable vector. KDF_{jt} denotes key developments by the brand j that owns focal nameplate i, $MEDF_{it}$ denotes media citations about recalls or acceleration for the focal nameplate i, $GENADSF_{it}$ denotes general ads by the focal nameplate i, $SALESADSF_{it}$ denotes sales ads by the focal nameplate i, $CHATF_{it}$ denotes concerns about the focal nameplate i, $CHATR_{rt}$ denotes concerns about the nearest rival r of the focal nameplate i, and $SALESF_{it}$ denotes sales of the focal nameplate i.

The matrices $\prod_l$ are 7 × 7 coefficient matrices, α_i denote unobserved nameplate-specific effects, λ_t denotes time effects, and e_{it} is a 7 × 1 vector of white-noise residuals. We model the contemporaneous effects in the variance–covariance matrix of the white-noise residuals (Luo 2009). We can impose a restriction that the underlying structure is the same for each cross-sectional unit (nameplate); that is, the coefficients in the matrices $\prod_l$ are the same for all the nameplates in our sample. However, because this assumption is most likely to be violated, we allow for "individual heterogeneity" in levels of the variables by introducing fixed effects, which is denoted by α_i in the model.

Thus, our model (Equation 6) is a system of dynamic panel data equations. Prior research has demonstrated that the fixed effects α_i are correlated with the regressors because of the lags of the dependent variables (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998). The usual "within" transformation to eliminate the fixed effects would create biased coefficients in this dynamic panel setting. Thus, we use the forward orthogonal deviations suggested by Arellano and Bover (1995) to eliminate the fixed effects. Also known as the Helmert transformation, this procedure removes only the forward mean, that is, the mean of all the future observations for each nameplate-month in our data set. This data transformation preserves the orthogonality between the transformed variables and the lagged regressor. Thus, we can use the lagged regressors as instruments and estimate the coefficients by system generalized method of moments (Arellano and Bover 1995). In addition, the use of forward orthogonal deviations does not induce autocorrelation in the error terms and frees us from serial correlation (Drakos and Konstantinou 2014). We use the program *pvar2* in Stata to estimate the PVAR (Love and Zicchino 2006).

In the PVAR for the Japanese brands, we use 39 nameplates because we have no rival nameplates for Nissan's 350Z and 370Z nameplates and because *Ward's* does not report sales for Toyota's Matrix nameplate. We use a lag of 3 according to the (Schwartz's) Bayesian information criterion and the ability of the model to converge. Our results remain the same whether we use a lag of 1 or 2. The parameter estimates of the PVAR are in Table M3 in Web Appendix M.

We find that concerns about the focal nameplate significantly decrease that nameplate's sales, with an elasticity of −4.3% (see "Japanese Brands" in Table 3). This number means a 1% increase in concerns about a nameplate decreases that nameplate's sales by 4.3%. Assuming monthly sales of 7,236 units for a nameplate (average sales across the 39 nameplates for the 15 months in our time frame), we find that a 1% increase in concerns about a nameplate in a month reduces that nameplate's monthly sales by 311 units. This translates into a loss of $8.6 million[10] for a nameplate in one month. More importantly, we find that concerns about the nearest rival significantly decrease the focal nameplate's sales, consistent with H_1. A 1% increase in the concerns about a nameplate's nearest rival decreases the focal nameplate's sales by 1.9%. Using the previous assumptions, we find that a 1% increase in concerns about a rival nameplate in a month decreases the focal nameplate's monthly sales by 137 units, which translates into a loss of $3.8 million for a nameplate in one month. The parameter estimates of the PVAR are shown in Table M4 in Web Appendix M.

Next, we report the results of the forecast error variance decomposition (FEVD). This analysis determines to what extent the endogenous variables contribute to the deviation in the focal nameplate's sales from its baseline expectations. The relative importance of the endogenous variables in the PVAR is established on the basis of FEVD values at 10 days, which reduces sensitivity to short-term fluctuations. Concerns about the focal nameplate explain relatively more of the variance of the focal nameplate's sales than concerns about the nearest rival (6.6% vs. 2.1%).

In the PVAR for Chrysler and Toyota, we use five nameplates out of the six produced by Chrysler because we could not identify a clear rival for Dodge from Toyota's list of nameplates. We use a lag of 3 according to the (Schwartz's) Bayesian information criterion and the ability of the model to converge. We find that concerns about the focal nameplate significantly decrease the focal nameplate's sales (see "Toyota and Chrysler" in Table 3). A 1% increase in concerns about a nameplate decreases that nameplate's sales by approximately 11%. Assuming monthly sales of 9,659 units for a nameplate (average sales across the 10 nameplates for the 15 months in our time frame) we find that a 1% increase in concerns about a nameplate in a month reduces monthly sales of the nameplate by 1,062 units. This translates into a loss of $29 million for a nameplate in one month due to concerns. Note that we use the negative online chatter about acceleration attribute here, and because of Toyota's acceleration issues during the study time frame, the effect of concerns on sales is much more potent in this PVAR model than the prior one. More importantly, we find that concerns about the nearest foreign rival significantly increase the focal nameplate's sales, consistent with H_2. A 1% increase in concerns about a nameplate's nearest rival from a different country increases the focal nameplate's sales by 2.2%. Using the same assumptions as previously, a 1% increase in concerns about a nameplate's nearest rival from a different country increases the focal nameplate's monthly sales by 212 units. This translates into a gain of $5.8 million for a focal nameplate in one month due to concerns about a rival's acceleration. As for the FEVD result, concerns about the focal nameplate explain much more of the variance in the focal nameplate's sales than concerns about the nearest rival brand from a different country (46% vs. 6%).

Effect on rival's stock market performance. We next test whether perverse halo affects a rival brand's stock market performance. An analysis at the nameplate level may be too noisy to find a pattern on stock market metrics (e.g., effect of concerns about Honda Ridgeline on Honda's abnormal returns), we aggregate the concerns about nameplates to the brand level for analyzing the effect of concerns about a recalled brand on a rival brand's abnormal stock returns. We use the VARX model to ascertain the relationship between concerns and stock returns. Similar to our prior

[10]We use an average new car price of $27,500 on the basis of average new car prices in 2009 and 2010; see http://www.usatoday.com/story/money/cars/2013/09/04/record-price-new-car-august/2761341/.

Table 3
AGGREGATE ANALYSIS OF SALES

	Japanese Brands		*Toyota and Chrysler*	
	Elasticity[a]	*Relative Importance*[b]	*Elasticity*[a]	*Relative Importance*[b]
Focal nameplate chatter	–4.3%***	6.6%***	–11.37%***	45.9%***
Nearest nameplate chatter	–1.9%***	2.1%***	2.16%*	6.4%*

*p < .05 (two-tailed test).
**p < .01 (two-tailed test).
***p < .001 (two-tailed test).
[a]Arc elasticity formula used to calculate elasticity (e.g., Trusov, Bucklin, and Pauwels 2009).
[b]We measure the relative importance using the forecast error variance decomposition technique (see Hanssens 1998 for a marketing application). The forecast error variance decomposition is like a partial R^2 (Stock and Watson 2001). Thus, relative importance is the improvement in R^2 in a PVAR model with versus without the focal independent variable. Table 3 denotes the marginal contribution of variables in explaining the variance in sales of the focal nameplate when the other endogenous variables are included in the model, that is, how much of the increase or decrease in sales of the focal nameplate is due to each row variable.

design, we estimate one VARX for the three Japanese brands and another VARX for Toyota and Chrysler. We include the same endogenous and exogenous variables as in the VARX models in the disaggregate analysis, but we aggregate the data to the brand level. However, we exclude the variables for sales and leasing ads for model parsimony. We include Toyota and Honda's abnormal returns in the VARX model for the Japanese brands but only Toyota's abnormal returns in the VARX model for Toyota and Chrysler, because only Toyota and Honda were traded on the American stock exchanges (NASDAQ, NYSE, and AMEX) during our study time frame. The VARX model includes both own-brand and across-brand effects of concerns on the abnormal stock returns. Therefore, the VARX model for the three Japanese brands includes abnormal returns for Toyota and Honda and concerns for Toyota, Honda, and Nissan. The VARX model for Toyota and Chrysler includes abnormal returns only for Toyota and concerns for Toyota and Chrysler. We use the Fama–French and Carhart four-factor model to calculate the abnormal returns. Because this model has been used in prior research (e.g., Tirunillai and Tellis 2012), we skip the details for brevity.

The optimal lag order is 1 for both the VARX models. The parameter estimates for the VARX model are in Table N1 in Web Appendix N. Figure 3, Panel A, illustrates the results of the effect of concerns about Toyota, Honda and Nissan concerns on Toyota's abnormal returns. A one-unit shock in concerns about Toyota has a decreasing impact on Toyota's abnormal returns, reaching its nadir on the fourth day, resulting in an accumulated effect of –42 basis points. One basis point is one-hundredth of a percentage. In dollar terms, this drop translates into a loss of approximately $17.1 million from Toyota's average market capitalization.[11] We find that a one-unit shock in concerns about Honda has a significant negative impact on Toyota's abnormal returns, with an accumulated effect of –18 basis points. In dollar terms, this drop translates into a loss of approximately $7.3 million from Toyota's average market capitalization. Thus, we find evidence of perverse halo in stock market performance, consistent with H_1. We do not find a significant effect of concerns about Nissan on Toyota's abnormal returns. Figure 3, Panel B, illustrates the results of the effect of concerns about Toyota, Honda, and Nissan on Honda's abnormal returns. None of the rival brands has a significant effect on Honda's abnormal returns. We find that concerns about Honda significantly reduce Honda's abnormal returns, with a cumulative impact of –21 basis points. In dollar terms, this translates into a loss of approximately $6.5 million from Honda's average market capitalization. Thus, Toyota shareholders suffered more from concerns about their own brand than did Honda's shareholders. Figure 3, Panel C, illustrates the results of the effect of concerns about Toyota and Chrysler on Toyota's abnormal returns. The parameter estimates for the VARX model are in Table N2 in Web Appendix N. We find that concerns about Chrysler increase Toyota's abnormal returns, with the effect reaching its peak on the second day, with an accumulated impact of 20 basis points. In dollar terms, this translates into a gain of approximately $8.2 million in Toyota's average market capitalization. Thus, we find evidence that country of origin moderates perverse halo on stock market performance, as it does for concerns, consistent with H_2.

Robustness Analysis

We carry out a set of robustness analyses such as using a different relevancy score for media citations and using television news sources other than ABC, and we estimate VARX equations between brands by size (small, medium, large) to establish the robustness of the results. Our results remain the same in these robustness tests. Web Appendix O reports the results of the robustness analysis.

DISCUSSION

Product recalls are one of the most common events that firms face. This study aims to find out whether recalls for nameplates of one brand can help or hurt other nameplates of the same brand or other brands. In particular, we estimate perverse halo, wherein negative chatter about one nameplate spills over into negative chatter about another nameplate. We focus on perverse halo in online chatter because it is temporally highly disaggregate (e.g., hours, days), passionate, instantaneous or live, pervasive, and relatively easily available. Furthermore, we analyze perverse halo at the nameplate level and evaluate how perverse halo affects downstream performance such as rivals' sales and stock market performance. This section summarizes the study findings, discusses some key issues, suggests implications, and lists the study limitations.

Summary of Findings

The key findings of the study are the following:

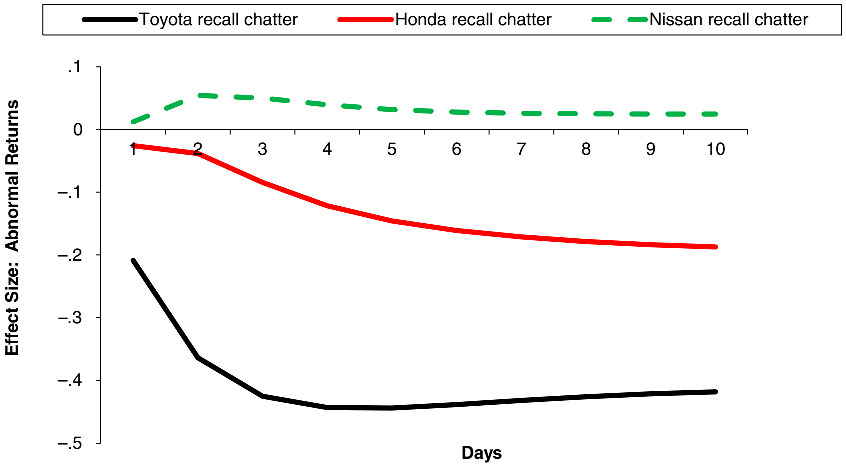
- Perverse halo is extensive. Between 67% and 74% of the effect of negative chatter is shared with one or more brands. That is, only 26%–33% of the effect of negative chatter is truly

[11]The accumulated effect in basis points is multiplied by the average number of outstanding shares and the average share price over the 470 days of our sample.

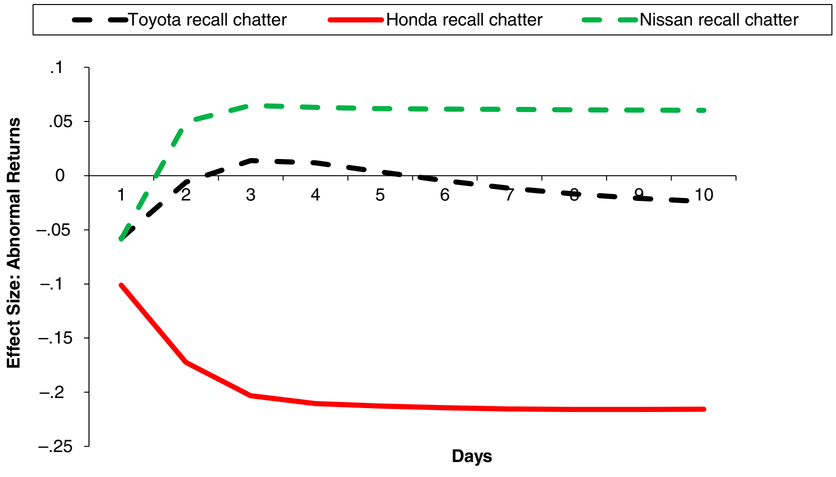
Figure 3

GRAPHS OF EFFECT OF NEGATIVE CHATTER ON STOCK MARKET RETURNS

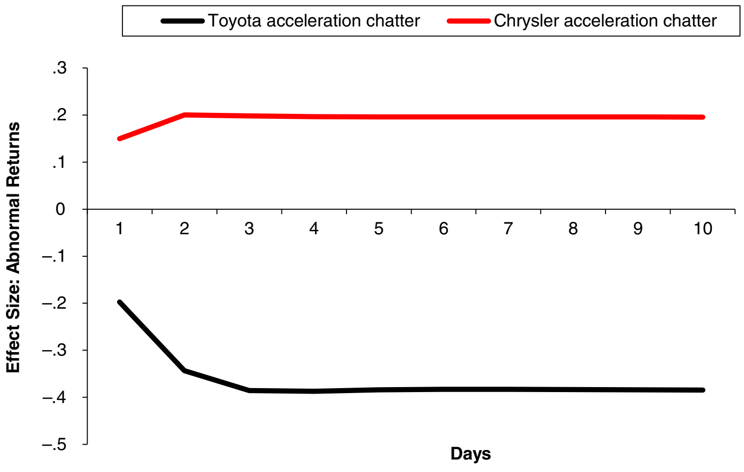
A: Cumulative Impulse Response of Negative Chatter (Recall) on Toyota's Abnormal Returns



B: Cumulative Impulse Response of Negative Chatter (Recall) on Honda's Abnormal Returns



C: Cumulative Impulse Response of Negative Chatter (Acceleration) on Toyota's Abnormal Returns



Notes: Solid lines indicate significance, and dashed lines indicate nonsignificance.

brand-specific. And within a brand, between 56% and 91% of the effect of negative chatter is shared among its nameplates. That is, perverse halo exists both for nameplates within the same brand and for nameplates across brands.
- The direction of perverse halo is asymmetric, with perverse halo being stronger from a dominant brand to a less dominant brand than vice versa.
- Perverse halo is strongest between brands that are from the same country.
- Perverse halo has a short wear-in period of 1 day and a modest wear-out period of about 6 days. However, even though these time lags seem short, concerns arise daily and, if unaddressed, can lead to persistent effects.
- Perverse halo affects performance metrics such as sales and stock market performance. A 1% increase in concerns about a rival nameplate leads to an average monthly loss in sales revenue of $3.8 million (elasticity of −1.9%) for a focal nameplate, and a one-unit shock in concerns about a rival brand erodes approximately $7.3 million (−18 basis points) from the focal brand's average market capitalization over 6 days.
- Online chatter amplifies the negative effect of recalls on downstream sales about 4.5 times.
- Apology advertising about recalls increases concerns for both the recalled brand and its rivals.

Implications

This study has the following implications. First, firms undergoing a crisis need to consider apology ads very carefully. In general, such ads can backfire because they increase attention to, evoking of, and elaboration about the crisis (Van Heerde, Helsen, and Dekimpe 2007; Siomkos and Shrivastava 1993). Indeed, we find that such ads increase concerns about not only the recalled brand but also its rivals.

Second, firms should keep an eye on recall events of rival firms from the same country and of similar size. We find that negative chatter about a nameplate of one brand spills over into negative chatter about nameplates of other brands, and this effect is aggravated for brands from the same country and of the same size as the recalled brand. Thus, we speculate that as soon as a rival has a recall, firms should lie low and avoid comparisons with firms that are undergoing a recall crisis, thereby minimizing perverse halo or negative spillover (Snyder, Higgins, and Stucky 1983). Social comparison theory suggests that firms can protect their image or status by avoiding comparisons with less reputable rivals (Snyder, Lassegard, and Ford 1986) or with rival firms undergoing a crisis. A denial strategy of stating that a firm's sourcing, manufacturing, designs, and scientific procedures have no link with the focal recall could backfire for the rival (Siomkos and Shrivastava 1993).

Third, we speculate that firms from a different country and of a different size than a recalled firm should emphasize their strengths and uniqueness when the recalled firm is under crisis (Hauser and Shugan 1983). Fourth, we speculate that firms need to give more thought to the role of consumer opinions in determining their rivals. This knowledge of consumer thinking will allow the firms to strategically deviate from consumer perspectives (Kim and Tsai 2012). If consumers think two firms are similar and comparable, the innocent rival faces the danger of receiving negative feedback when the other has a recall. Thus, firms may need to deviate from their current positioning and appear unique. Prior research has shown that comparative advertising increases consumers' perceptions of similarity between firms (Gorn and Weinberg 1984; Kim and Tsai 2012).

Fifth, marketing managers of recalled firms need to monitor and manage chatter on social media during product recalls. We find that negative online chatter can amplify the negative effect of product recalls on sales. We call this the "word-of-mouth multiplier" (Goldenberg et al. 2007). We find that the elasticity of the focal nameplate's recall event on the focal nameplate's sales is −2.2% for the PVAR model that includes only the recall event and sales of the focal nameplate, whereas the elasticity of the recall event on sales becomes −9.5% when the two chatter metrics are included in the PVAR model.[12] Thus, the effect of the focal nameplate's recall event on its own sales gets amplified about 4.5 times, from 2.2 to 9.5, because of negative chatter about both the focal and rival nameplates. Note that this specification does not include other variables that could affect the focal nameplate's sales as in our formal PVAR analysis of chatter on sales, so the estimates that we report may be a little liberal.

Thus, we speculate that during crisis situations, it is imperative for firms to communicate with consumers in the right way, such as placating various concerns. Firms often focus only on mass media as an external factor that influences consumers. Thus, they adopt communication strategies to manage mass media (Siomkos and Shrivastava 1993). However, the ubiquity of social media has created new challenges. Firms need to handle the spread of information about product recalls in social media. Concerns about a firm can diffuse to a wider audience in seconds and have high acceptances by fellow consumers. Thus, as a first step, firms could relay the information about the recall to all important social media sites, have a comprehensive set of FAQs, and ensure that all searches for information about the recall are directed to one place (e.g., a microsite dedicated to the recall).

Finally, we speculate that firms should know the hashtags and keywords being used to discuss recalls in social media. Identifying the hashtags and keywords can enable managers to track mentions about the recall in the social media space (Fisher 2012). Firms can subsequently engage in a two-sided dialogue in these important social media sites to allay specific concerns. This dialogue could mitigate the tide of concerns that can diffuse beyond one network. For example, social media or online communities managers could provide clear information about the recall and steps taken to reduce the hazards, and address specific concerns directly either in their microsite or through their own blogs,

[12]To compute this multiplier, we ran the following analysis. We first ran a PVAR model with the same sample of nameplates as in our aggregate analysis but with the focal nameplate's recall event and sales as the only endogenous variables. We imposed the following ordering of variables: (1) focal nameplate's recall event and (2) focal nameplate's sales. We chose this ordering so that the recall event occurred first, which then affected sales. We next ran another PVAR with the following endogenous variables, ordered as follows: (1) focal nameplate's recall event, (2) focal nameplate's recall chatter, (3) rival nameplate's recall chatter, and (4) focal nameplate's sales. The latter model included the direct effect of the focal nameplate's recall event on sales plus the indirect effect of the focal nameplate's recall event on sales through the direct effect of the focal nameplate's recall event on the focal nameplate's chatter and the rival nameplate's chatter and the direct effect of the focal nameplate's chatter and the rival nameplate's chatter on the focal nameplate's sales.

social network accounts (e.g., Facebook groups, Twitter accounts, Facebook apps), and forums and address concerns as they come up.

Limitations

This study has some limitations that could be the basis for further research. First, we restricted our focus to the automobile industry because of its high frequency of recalls and availability of online chatter. It would be worthwhile to investigate the generalizability of the results to other product categories. Second, we assume that that online chatter, advertising, and media presence of nameplates produced by other brands have zero effect on the online chatter, advertising, and media presence of Toyota, Honda, Nissan, or Chrysler. An absence of these nameplates could produce omitted variable bias in the estimates. Nevertheless, what we have are still important and well-known brands that provide many insights. Likewise, a number of articles in marketing have used only one or two firm rivals rather than including every possible rival (e.g., Joshi and Hanssens 2010; Tirunillai and Tellis 2012).

REFERENCES

Andrews, Wilson and Gregor Aisch (2014), "A Record Year for Auto Recalls," *New York Times*, (December 30), [available at http://www.nytimes.com/interactive/2014/12/30/business/a-record-year-for-auto-recalls.html?_r=0].

Arellano, Manuel and Stephen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 58 (2), 277–97.

——— and Olympia Bover (1995), "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics*, 68 (1), 29–51.

Asur, Sitaram and Bernardo Huberman (2010), "Predicting the Future with Social Media," Technical Report No. HPL-2010-53, HP Labs, [available at http://www.hpl.hp.com/techreports/2010/HPL-2010-53.html].

Bae, Yong-Kyun and Hugo Benítez-Silva (2013), "The Effects of Automobile Recalls on the Severity of Accidents," *Economic Inquiry*, 51 (2), 1232–50.

Barsalou, Lawrence W. (1992), *Cognitive Psychology: An Overview for Cognitive Psychologists*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Blackshaw, Pete and Mike Nazzaro (2006), *Consumer-Generated Media (CGM) 101: Word-of-Mouth in the Age of the Web-Fortified Consumer*, 2nd ed. New York: BuzzMetrics.

Blundell, Richard and Stephen Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87 (1), 115–43.

Chen, Yubo, Shankar Ganesan, and Yong Liu (2009), "Does a Firm's Product Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises," *Journal of Marketing*, 73 (November), 214–26.

Chevalier, Judith A. and Dina Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research*, 43 (August), 345–54.

Choi, Yoonhyeung and Ying-Hsuan Lin (2009), "Consumer Responses to Mattel Product Recalls Posted on Online Bulletin Boards: Exploring Two Types of Emotion," *Journal of Public Relations Research*, 21 (2), 198–207.

Chow, Stirling and Peter Rodgers (2005). "Constructing Area-Proportional Venn and Euler Diagrams with Three Circles," paper presented at Euler Diagrams workshop, Paris (September 29–30), [available at http://kar.kent.ac.uk/14285/].

Chu, Ting-Heng, Che-Chun Lin, and Larry J. Prather (2005), "An Extension of Security Price Reactions Around Product Recall Announcements," *Quarterly Journal of Business and Economics*, 44 (3/4), 33–47.

Cleeren, Kathleen, Marnik G. Dekimpe, and Kristiaan Helsen (2008), "Weathering Product-Harm Crises," *Journal of the Academy of Marketing Science*, 36 (2), 262–70.

Collins, Allan M. and Elizabeth F. Loftus (1975), "A Spreading-Activation Theory of Semantic Processing," *Psychological Review*, 82 (6), 407–28.

Dawar, Niraj (1998), "Product-Harm Crises and the Signaling Ability of Brands," *International Studies of Management and Organization*, 28 (3), 109–19.

——— and Madan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 37 (May), 215–26.

Deighton, John A. and Leora Kornfeld (2008), "Obama Versus Clinton: The YouTube Primary," Case No. 509-032, Harvard Business School (October).

——— and ——— (2010), "United Breaks Guitars," Case No. 510-057, Harvard Business School (January).

Dekimpe, Marnik G. and Dominique M. Hanssens (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1–21.

Dellarocas, Chrysanthos, Xiaoquan Michael Zhang, and Neveen F. Awad (2007), "Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures," *Journal of Interactive Marketing*, 21 (4), 23–45.

Drakos, Konstantinos and Panagiotis T. Konstantinou (2014), "Terrorism, Crime, and Public Spending: Panel VAR Evidence from Europe," *Defence and Peace Economics*, 25 (4), 349–61.

Farquhar, Peter H., Paul M. Herr, and Russell H. Fazio (1990), "A Relational Model for Category Extensions of Brands," *Advances in Consumer Research*, 17 (1), 856–60.

Fazio, Russell H. (1987), "Category-Brand Associations and Their Activation from Memory," working paper, Ogilvy Center for Research and Development.

Feldman, Jack M. and John G. Lynch (1988), "Self-Generated Validity and Other Effects of Measurement on Belief, Attitude, Intention, and Behavior," *Journal of Applied Psychology*, 73 (3), 421–35.

Fisher, Tia (2012), "Tips for Using Social Media in Product Recall," *Emoderation*, (April 20), [available at http://www.emoderation.com/tips-for-using-social-media-in-product-recall-3/].

Goldenberg, Jacob, Barak Libai, Sarit Moldovan, and Eitan Muller (2007), "The NPV of Bad News," *International Journal of Research in Marketing*, 24 (3), 186–200.

Gorn, Gerald J. and Charles B. Weinberg (1984), "The Impact of Comparative Advertising on Perception and Attitude: Some Positive Findings," *Journal of Consumer Research*, 11 (2), 719–27.

Granger, Clive W.J. (1969), "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica*, 37 (3), 424–38.

——— and Paul Newbold (1986), *Forecasting Economic Time Series*, 2d ed. Orlando, FL: Academic Press.

Greto, Michael, Andreas Schotter, and Mary B. Teagarden (2010), "Toyota: The Accelerator Crisis," Case No. TB0243, Thunderbird School of Global Management.

Hanssens, Dominique M. (1998), "Order Forecasts, Retail Sales, and the Marketing Mix for Consumer Durables," *Journal of Forecasting*, 17 (34), 327–46.

Hauser, John R. and Steven M. Shugan (1983), "Defensive Marketing Strategy," *Marketing Science*, 2 (4), 319–60.

Hof, Rob (2005), "Inside 'Dell Hell,'" *BusinessWeek*, (September 29), [available at http://www.businessweek.com/the_thread/techbeat/archives/2005/09/inside_dell_hel.html].

Holtz-Eakin, Douglas, Whitney Newey, and Harvey S. Rosen (1988), "Estimating Vector Autoregressions with Panel Data," *Econometrica*, 56 (6), 1371–95.

Hong, Sung-Tai and Robert S. Wyer Jr. (1989), "Effects of Country-of-Origin and Product-Attribute Information on Product Evaluation: An Information Processing Perspective," *Journal of Consumer Research*, 16 (2), 175–87.

——— and ——— (1990), "Determinants of Product Evaluation: Effects of the Time Interval Between Knowledge of a Product's Country of Origin and Information About Its Specific Attributes," *Journal of Consumer Research*, 17 (3), 277–88.

Hora, Manpreet, Hari Bapuji, and Aleda V. Roth (2011), "Safety Hazard and Time to Recall: The Role of Recall Strategy, Product Defect Type, and Supply Chain Player in the U.S. Toy Industry," *Journal of Operations Management*, 29 (7), 766–77.

Janakiraman, Ramkumar, Catarina Sismeiro, and Shantanu Dutta (2009), "Perception Spillovers Across Competing Brands: A Disaggregate Model of How and When," *Journal of Marketing Research*, 46 (August), 467–81.

Jensen, Christopher (2011), "2010 a Record Year for 'Voluntary' Recalls," Wheels (blog), (January 20), [available at http://wheels.blogs.nytimes.com/2011/01/20/2010-a-record-year-for-voluntary-recalls/].

Joshi, Amit and Dominique M. Hanssens (2010), "The Direct and Indirect Effects of Advertising Spending on Firm Value," *Journal of Marketing*, 74 (January), 20–33.

Kalaignanam, Kartik, Tarun Kushwaha, and Meike Eilert (2013), "The Impact of Product Recalls on Future Product Reliability and Future Accidents: Evidence from the Automobile Industry," *Journal of Marketing*, 77 (March), 41–57.

Kim, Kwang Ho and Wenpin Tsai (2012), "Social Comparison Among Competing Firms," *Strategic Management Journal*, 33 (2), 115–36.

Kraljic, Peter (1983), "Purchasing Must Become Supply Management," *Harvard Business Review*, 61 (5), 109–17.

Kwak, Haewoon, Changhyun Lee, Hosung Park, and Sue Moon (2010), "What Is Twitter, a Social Network or a News Media?" in *Proceedings of the 19th International Conference on World Wide Web*. New York: Association for Computing Machinery, 591–600.

Lithium (2014), "9 Big Reasons for Serious WOMM," (accessed February 1, 2016), [available at http://aci.info/wp-content/uploads/2014/02/lithium-wom-marketing-infographic.png].

Liu, Yong (2006), "Word-of-Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing*, 70 (July), 74–89.

Loken, Barbara and James Ward (1990), "Alternative Approaches to Understanding the Determinants of Typicality," *Journal of Consumer Research*, 17 (2), 111–26.

Love, Inessa and Lea Zicchino (2006), "Financial Development and Dynamic Investment Behavior: Evidence from Panel VAR," *Quarterly Review of Economics and Finance*, 46 (2), 190–210.

Luo, Xueming (2009), "Quantifying the Long-Term Impact of Negative Word of Mouth on Cash Flow and Stock Price Volatility," *Marketing Science*, 28 (1), 148–65.

Maheswaran, Durairaj (1994), "Country of Origin as a Stereotype: The Effects of Consumer Expertise and Attribute Information on Product Evaluations," *Journal of Consumer Research*, 21 (2), 354–65.

——— and Cathy Yi Chen (2006), "Nation Equity: Incidental Emotions in Country-of-Origin Effects," *Journal of Consumer Research*, 33 (3), 370–76.

McCombs, Maxwell E. and Donald L. Shaw (1972), "The Agenda-Setting Function of Mass Media," *Public Opinion Quarterly*, 36 (2), 176–87.

Newey, Whitney K. and Kenneth D. West (1987), "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55 (3), 703–08.

Nielsen (2011), "State of the Media: Social Media Report Q3," (September 11), [available at http://www.nielsen.com/us/en/insights/reports/2011/social-media-report-q3.html].

Nijs, Vincent R., Shuba Srinivasan, and Koen Pauwels (2007), "Retail-Price Drivers and Retailer Profits," *Marketing Science*, 26 (4), 473–87.

Olivares, Marcelo and Gérard P. Cachon (2009), "Competing Retailers and Inventory: An Empirical Investigation of General Motors' Dealerships in Isolated U.S. Markets," *Management Science*, 55 (9), 1586–1604.

Pauwels, Koen, Dominique M. Hanssens, and S. Siddarth (2002), "The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity," *Journal of Marketing Research*, 39 (4), 421–39.

——— and Shuba Srinivasan (2004). "Who Benefits from Store Brand Entry?" *Marketing Science*, 23 (3), 364–90.

Peters, J. (2005), "More Complex Cars and Stricter Rules Lead to More Recalls," *New York Times*, (October 26), [available at http://www.nytimes.com/2005/10/26/automobiles/autospecial/26peters.html?pagewanted=all].

Quelch, John A., Carin-Isabel Knoop, and Ryan Johnson (2010). "Toyota Recalls (A): Hitting the Skids," Case No. 9-511-016, Harvard Business School.

Rhee, Mooweon and Pamela R. Haunschild (2006), "The Liability of Good Reputation: A Study of Product Recalls in the U.S. Automobile Industry," *Organization Science*, 17 (1), 101–17.

Roehm, Michelle L. and Alice M. Tybout (2006), "When Will a Brand Scandal Spill Over, and How Should Competitors Respond?" *Journal of Marketing Research*, 43 (August), 366–73.

Ross, Brian, Joseph Rhee, Angela M. Hill, and Megan Chuchmach (2009), "Owners of Toyota Cars in Rebellion over Series of Accidents Caused by Sudden Acceleration," *ABC News*, (November 3), [available at http://abcnews.go.com/Blotter/RunawayToyotas/sudden-acceleration-toyota-cars-owners-rebel-accidents/story?id=8980479].

Shepardson, David (2015), "Recall Woes Follow GM into New Year," *Detroit News*, (January 1), [available at http://www.detroitnews.com/story/business/autos/general-motors/2015/01/01/gm-recalls-suvs-trucks-ignition-issue/21149405/].

Sims, Christopher A. and Tao Zha (1999), "Error Bands for Impulse Responses," *Econometrica*, 67 (5), 1113–55.

Siomkos, George and Paul Shrivastava (1993), "Responding to Product Liability Crises," *Long Range Planning*, 26 (5), 72–79.

Smith, Edward E. and Douglas L. Medin (1981), *Categories and Concepts*. Cambridge, MA: Harvard University Press.

Snyder, Charles Richard, Raymond L. Higgins, and Rita J. Stucky (1983), *Excuses: Masquerades in Search of Grace*. New York: John Wiley & Sons.

———, Mary Anne Lassegard, and Carol E. Ford (1986), "Distancing After Group Success and Failure: Basking in Reflected

Glory and Cutting off Reflected Failure," *Journal of Personality and Social Psychology*, 51 (2), 382–88.

Sorrel, Charlie (2010), "iPhone 4 Loses Reception When Holding It by Antenna Band?" *Wired*, (June 24), [available at http://www.wired.com/2010/06/iphone-4-loses-reception-when-antenna-band-is-touched-firmware-issue/].

Stephen, Andrew T. and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49 (October), 624–39.

Stock, James H. and Mark W. Watson (2001), "Vector Autoregressions," *Journal of Economic Perspectives*, 15 (4), 101–15.

Tellis, Gerard J. and Philip Hans Franses (2006), "Optimal Data Interval for Estimating Advertising Response," *Marketing Science*, 25 (3), 217–29.

Tirunillai, Seshadri (2014), "Mining Marketing Meaning from Online Chatter: Strategic Brand Analysis of Big Data Using Latent Dirichlet Allocation," *Journal of Marketing Research*, 51 (August), 463–79.

——— and Gerard J. Tellis (2012), "Does Chatter Really Matter? Impact of User Generated Content on Stock Market Performance," *Marketing Science*, 31 (2), 198–215.

Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing*, 73 (September), 90–102.

Van Heerde, Harald, Kristiaan Helsen, and Marnik G. Dekimpe (2007), "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230–45.

WardsAuto (2010/2011), *Ward's Automotive Yearbook*, Alan K. Binder, ed. Southfield, MI: Wards Communications.

Yang, Yufeng and Weiping Yu (2014), "Brand Scandals Spillover Model Based on the GMDH," in *Proceedings of the Seventh International Conference on Management Science and Engineering Management*. Berlin: Springer, 591–601.

Zellner, Arnold (1962), "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," *Journal of the American Statistical Association*, 57 (298), 348–68.