Does Deceptive Marketing Pay? The Evolution of Consumer Sentiment Surrounding a Pseudo-Product-Harm Crisis

Working Paper · October 2017

DOI: 10.13140/RG.2.2.32244.55687

4 authors, including:

Ho Kim
University of Missouri - St. Louis

Gene Moo Lee
University of British Columbia - Vancouver

Evolution of Consumer Sentiment Surrounding a Pseudo-Product-Harm Crisis: The Impact of Advertising and News Sentiment

September 2016

Reo Song
Assistant Professor of Marketing
1250 Bellflower Blvd., CBA 354, Department of Marketing
California State University, Long Beach, CA 90840
Email: reo.song@csulb.edu

Ho Kim
Assistant Professor of Digital and Social Media Marketing
1 University Boulevard, Tower 1310
University of Missouri – St. Louis, MO 63121
Email: kimho@umsl.edu

Gene Moo Lee
Assistant Professor of Information Systems
701 S. West St. Suite 516
The University of Texas at Arlington, TX 76019
Email: gene.lee@uta.edu

Sungha Jang
Assistant Professor of Marketing
1301 Lovers Lane, 3048 Business Building
Kansas State University, Manhattan, KS 66506
Email: sjang@ksu.edu

* We thank Taeho Song for providing a part of data used for this research.

Abstract

Pseudo-product-harm crises, resulting from false claims about a firm's products, pose significant challenges to firms. Unlike traditional product-harm crises, a firm involved in a pseudo-product-harm crisis can suffer from substantial damage until or even after the truth emerges. Using a pseudo-product-harm crisis event that involves two competing firms, this research examines how consumer sentiments evolve surrounding the crisis in response to the firms' advertising (as paid media) and news publicity (as earned media). Our analyses show that while both firms suffer, the damage is larger to the offending firm (which causes the crisis) than to the victim firm (which suffers from the false claim) in terms of advertising effectiveness and negative news publicity. Our study indicates that apart from the ethical concern, false claims about competing firms are not an effective business strategy to increase firm performance.

keywords: pseudo-product-harm crisis, deceptive marketing, unethical business practice, advertising strategy, topic modeling, sentiment analysis, text mining

Introduction

Product-harm crises refer to incidents created by defective or dangerous products. There have been many product-harm crises that have imperiled customers and companies such as Kraft's Salmonella Peanut Butter (2007), Mattel's toys with lead paint (2007), Toyota's sticky gas pedals (2010), Takata's defective airbag (2013–present), GM faulty ignition switch (2015), and Volkswagen's emission scandal (2015). Because product-harm crises are harmful to customer well-being and threaten companies (Dawar and Pillutla 2000; Van Heerde, Helsen, and Dekimpe 2007), they negatively affect sales, advertising effectiveness, and firm value (Chen, Ganesan, and Liu 2009; Cleeren, van Heerde, and Dekimpe 2013).

Similarly, firms often suffer from pseudo-product-harm crises that stem from false claims about their products or adverse rumors by either consumers or competitors (Tybout, Calder, and Sternthal 1981). For example, in March 2005, a customer reported that she found a human fingertip in a bowl of beef chili at a Wendy's store, leading Wendy's stock price to drop almost 10% and sales in the San Francisco Bay area to fall by about 30%. Yet the claim turned out to be false and the woman was arrested for attempted grand larceny a month later (*Financial Times* 2005). In June 2015, KFC sued three Chinese companies for spreading rumors through social media that its chickens had eight legs, and sought compensation of up to 1.5 million yuan (about $245,000) from each company, an apology, and an end to the alleged practices (*The Wall Street Journal* 2015). A pseudo-product harm crisis is also common in political campaigns. When John McCain ran for the Republican Party nomination during the 2000 presidential election against Texas Governor George W. Bush and won the New Hampshire primary, the Bush campaign famously ran smear campaigns that publicized false claims that McCain had fathered a child out of wedlock, was gay, and was married to a drug addict—even as the Bush campaign strongly

denied any involvement in those attacks. The truth was revealed later, but the harm to McCain's campaign had already been done, and McCain withdrew from the race soon thereafter (*New York Times* 2007; *Vanity Fair* 2004).

Pseudo-product-harm crises are different from actual product harm crises. A pseudo-product-harm crisis often involves a competing firm, i.e., the offending firm which causes the crisis, as well as the victim firm which suffers from the false claim. Thus, pseudo–product-harm crisis management likely differs from the strategies applied to manage actual product harm crises. To formulate a good crisis management strategy in a pseudo product harm crisis, it is critical to understand how consumer sentiment evolves surrounding such a crisis. Especially, understanding how online consumer opinions respond to firms' advertising and media publicity is essential, given the increasing importance of online word of mouth. However, research on pseudo-product harm crises has been scarce, limiting our understanding on this subject. To broaden our perspective on product harm crises and to help firms involved in a pseudo-product harm crisis develop an effective crisis management strategy, we examine how consumer sentiment about two competing firms evolves before, during, and after a pseudo product harm crisis in response to the firms' advertising and media publicity.

Our empirical analyses suggest that the offending firm suffers more than the victim firm in a pseudo product harm crisis. While the advertising effectiveness of the victim firm does not change, the effect of the offending firm's advertising on consumer sentiment diminishes or turns even negative during and after the crisis. The victim firm also suffers. Increased negative news sentiments during the crisis are associated with a higher level of negative consumer sentiments. However, this is also true to the offending firm. During the crisis, negative news sentiment significantly increases, which leads to increased negative consumer sentiment. While positive

news sentiments are associated with reduced negative consumer sentiments during the event, this effect is much smaller than the undesirable effect from negative news sentiments due to significantly increased negative news volume. The fact that both firms suffer from the negative news publicity implies that firms experiencing a pseudo-product-harm crisis should focus on developing a suitable news media strategy instead of advertising strategy. Especially, for the offending firm, advertising can backfire and aggravate the situation.

However, while both firms are impaired from a pseudo-product-harm-crisis, the damage is bigger to the offending firm. Thus, in addition to ethical concerns, it does not seem to be a good business tactic to cause a pseudo-product-harm-crisis to hurt competing firms. Research in deceptive marketing provides similar implications. Prior research has documented that consumers' perceptions of deceptive practices lead to negative consequences for the firm, such as customer dissatisfaction, negative word-of-mouth, and distrust (Riquelme, Román, and Iacobucci 2016). In line with these studies, our results suggest that deceptive marketing through a pseudo-product crisis can undermine the effectiveness of advertising by negatively affecting consumer sentiment.

Our study provides important implications on the debate on corporate social responsibility (CSR) and corporate hypocrisy. Business has increasingly been viewed as a major cause of social, environmental, and economic problems (Porter and Kramer 2011). Many companies have responded to this declining trust by embracing CSR, but a large number of businesses still remain in the narrowly defined, outdated profit maximization framework. They try to optimize short-term financial performance and overlook the well-being of their customers and society. In addition, the inconsistencies between the promise of CSR communicated by the firm and the actual business practices revealed from other sources have negatively affected

firms' reputation and financial performance (Wagner, Lutz and Weitz 2009). Trying to maximize short-term profits through false claims or deceptive marketing hurts both the victim, the offender, and, ultimately the consumer. Studies have shown that doing good can benefit both society and the firm (e.g., Luo and Bhattacharya 2009). Our research shows that doing bad hurts both society and the firm. In the next section, we briefly discuss the importance of online word of mouth and consumer sentiment to motivate our study.

Literature Review

Consumer sentiment and online word-of-mouth

The big data revolution has become a fundamental driving force of societal changes in the information age (Ross 2016). Data revolution has made available unprecedented amounts of data in various formats. A prominent example is online word of mouth data expressed in various social media platforms, an unstructured, text-heavy form of data. Online word of mouth has become a critical component of firms' marketing strategy as the Internet has emerged as a leading communication platform (Divol, Edelman, and Sarrazin 2012). Research finds that online consumer reviews are a significant determinant of product revenues (Duan, Gu, and Whinston 2008; Lu et al. 2013), profitability (Rishika et al. 2013), and firm value (Luo, Zhang, and Duan 2013). Thus, investigating the determinants of consumer word of mouth is critical (Meyer, Song, and Ha 2016). Noting that improved predictive power of consumer ratings would lead to a revenue increase, Netflix held a $1 million prize contest to enhance the predictive accuracy of its existing rating algorithm. Recognizing that more and more consumers rely on word of mouth and recommendations by other consumers in their purchase decisions, Amazon reportedly paid $150 million to acquire Goodreads (*The Atlantic* 2013), an online book review

site. Academic scholars have also noticed that online word of mouth increasingly assumes the role of traditional marketing. Using consumer reviews in Yelp.com, Luca (2011) finds that the positive effect of consumer reviews on restaurant demand is mostly driven by independent restaurants and that the market share of chain restaurants has declined as Yelp penetration has increased. The significance of consumer reviews is also found in various product categories such as books (Chevalier and Mayzlin 2006), movies (Dellarocas, Zhang, and Awad 2007), TV shows (Godes and Mayzlin 2004), and alcohol (Clemons, Gao, and Hitt 2006). Besides the direct impact to the focal products, online product reviews can affect the purchase of related products (e.g., substitutes and complements) in the consumers' consideration sets (Kwark et al. 2016). These findings suggest that online word of mouth can partially substitute the role of brand reputation (Simonson and Rosen 2014).

With the advent of social media such as blogs and online communities, firms' media strategies have been experiencing a dramatic change. Prior studies distinguish media types into paid (e.g., advertising) and earned (e.g., blogs and newspapers) media (e.g., Kim and Hanssens 2016; Onishi and Manchanda 2012; Stephen and Galak 2012). Given the increasing role of online word of mouth in consumer purchase decisions, understanding how different types of media affect online consumer sentiment is important to develop effective communication strategies. Recent research suggests that word of mouth has a greater impact on consumer decisions and information search than advertising and media publicity (Goh, Heng, and Lin 2013; Kim and Hanssens 2016; Trusov, Bucklin, and Pauwels 2009). This is probably because consumers trust word of mouth and recommendations by other consumers more than firm-initiated advertising (A.C. Nielsen Report 2012; Burmester et al. 2015). Consumers tend to think

of product information provided by word of mouth as neutral and objective compared to the information contained in advertising, which is driven by profit motives.

Online word of mouth is important, particularly in a product-harm crisis situation because many consumers will actively seek information relevant to the product-harm crisis such as risks of using the product. Because today's online communication platforms can spread damage from product harm crises more extensively, firms need to effectively manage consumers' online engagement in such a crisis. A recent example is General Motors' recall of 1.6 million vehicles in 2014. The company preemptively monitored hundreds of websites and replied to thousands of angry customers through social media platforms such as Facebook, Twitter, and Instagram (*The Wall Street Journal* 2014). Another example is the Gap Inc.'s decision to scrap its new logo design and revert to its original logo within a week faced with scathing online sentiment from thousands of consumers. By recognizing that consumer online sentiment represented an important warning signal of potential issues, the company could prevent an actual crisis (*Sentinel Projects* 2010). Against this backdrop, our study investigates the impact of advertising and news publicity on consumer sentiment surrounding a pseudo-product-harm crisis, an area not thoroughly studied by prior research.

Advertising and news publicity

Our study focuses on the two types of media that can influence consumer word of mouth and sentiment during a pseudo-product-harm crisis: advertising as paid media and news publicity as earned media. Advertising can be used to restore a positive image and help foster an effective response strategy to a product harm crisis (Cowden and Sellnow 2002; Kim and Choi 2014). However, it may be counterproductive if used improperly (Tybout, Calder, and Sternthal 1981). In 2010, British Petroleum (BP) spent nearly $100 million on advertising, three times more than

it spent during the same period in the previous year, to respond to the Deepwater Horizon oil spill (*The Wall Street Journal* 2010). However, its advertising campaign largely backfired and the company faced severe criticism from consumers and environmental groups who thought BP should have better spent the money cleaning up the spill and compensating victims (*Business Insider* 2010).

Advertising strategy can be more complicated when several companies are involved in the crisis. When a company suffers a scandalous crisis, the outcomes might benefit competing brands because consumers might seek to switch to other brands. For example, Goodyear and Michelin tires both experienced sales increases after the Firestone tire crisis in 2000 (Roehm and Tybout 2006). An offending firm might reduce its advertising expenditures hoping that the public will forget about the product-harm crisis. In contrast, competitors may increase their advertising expenditures to take advantage of the situation. A crisis can also cause negative spillover effects to the industry if consumers lose trust in the industry (Borah and Tellis 2016). For example, the Enron scandal created negative spillover to the energy industry. In such a case, the focal firm and competitors experiencing the crisis likely change their marketing strategies (van Heerde, Helsen, and Dekimpe 2007; Zhao, Zhao, and Helsen 2011). Similarly, understanding how consumers feel about the firms suffering from a pseudo-product-harm crisis is vital not only to the focal firms, but also to the firms in the same industry.

In addition to advertising, news coverage and publicity can affect consumer sentiment during and after the crisis. While many studies have examined the impacts of advertising and word of mouth on firms' performance metrics (e.g., Bruce, Foutz, and Kolsarici 2012; Villanueva, Yoo, and Hanssens 2008), scholars have paid much less attention to news publicity than other forms of media. In addition, most existing research has typically examined the effect

of earned media (i.e., word of mouth or press coverage) in isolation (e.g., Ahluwalia, Burnkrant, and Unnava 2000; Berger, Sorensen, and Rasmussen 2010). A few exceptions include Stephen and Galak (2012) who have examined how two types of earned media, news publicity and social media, affect sales and activity in each other. Another study that has investigated advertising and media coverage together is Van Heerde, Gijsbrechts, and Pauwels (2015). They have examined how media coverage of a price war affects market share and the competing firms' advertising and price strategy. Our study combines paid media (i.e., advertising) and the types of earned media (i.e., news publicity and social media) to examine how sentiment expressed in press coverage and firms' advertising affect consumer sentiment revealed in social media.

Deceptive marketing

Pseudo-product-harm crises result from false claims about a firm's products, thus can be understood in the context of deceptive marketing. Compared to the positive effects of marketing activities, academic scholars have paid less attention to the consequences of deceptive marketing. However, understanding the effect of deceptive marketing is important given that negative information is often more salient than positive information to consumers (e.g., Ahluwalia 2002; Herr, Kardes, and Kim 1991).

Once the truth is revealed, the consequences of deceptive marketing can be significantly negative. Tipton, Bharadwaj, and Robertson (2009) find that the regulatory exposure of deceptive marketing negatively affects firm value even though the event carries no direct cost to the firm. In addition, the negative effect of deceptive marketing can spill over to the general marketing communication and other products because consumers may become skeptical about not only the specific product involved, but also the entire firm. A study by Darke and Ritchie (2007) shows that advertising deception produces a negative bias in consumers' attitudes toward

subsequent advertisements across different geographical regions, different kinds of products, and different types of claims. They further report that these generalized negative effects occur because advertising deception activates negative stereotypes about advertising and marketing in general.

Our study also sheds light on the negative spillover of deceptive marketing. Not only the offending firm's advertising effectiveness suffered, but also the number of its franchise stores declined (Maeil Business Newspaper 2011). This fact suggests that negative consumer sentiment transfers to the entire firm's reputation even if the deceptive marketing was used by a franchise owner instead of the management of the offending firm.

Model

To examine how advertising influences brand sentiment before and after the pseudo-product-harm-crisis, we estimate Equations (1) – (4). We estimate them year by year to compare the effect of advertising before (2009), during (2010), and after (2011) the event. We use only the fourth quarter data because the two firms' advertising expenditures are mostly concentrated on this period each year.[1]

$$(1)\quad BLOGPOS_{y,t}^{P} = \beta_{y,0}^{PPOS} + \beta_{y,1}^{PPOS}\log\left(TVAD_{y,t}^{P}\right) + \beta_{y,2}^{PPOS}\log\left(NEWSPOS_{y,t-1}^{P}\right) + \beta_{y,3}^{PPOS}\log\left(NEWSNEG_{y,t-1}^{P}\right) + \beta_{y,4}^{PPOS}BREADPOS_{y,t}^{P} + \beta_{y,5}^{PPOS}MON + \cdots + \beta_{y,10}^{PPOS}SAT + \varepsilon_{y,t}^{PPOS}$$

$$(2)\quad BLOGNEG_{y,t}^{P} = \beta_{y,0}^{PNEG} + \beta_{y,1}^{PNEG}\log\left(TVAD_{y,t}^{P}\right) + \beta_{y,2}^{PNEG}\log\left(NEWSPOS_{y,t-1}^{P}\right) + \beta_{y,3}^{PNEG}\log\left(NEWSNEG_{y,t-1}^{P}\right) + \beta_{y,4}^{PNEG}BREADPOS_{y,t}^{P}$$

[1] As bakery sales in Korea are concentrated in the fourth quarters, Korean bakery companies adopt pulsing strategy for advertising schedule (Sissors and Baron 2010), executing the majority of their advertising during the last three months of each year.

$$+\beta_{y,5}^{PNEG} MON + \cdots + \beta_{y,10}^{PNEG} SAT + \varepsilon_{y,t}^{PNEG}$$

(3) $$BLOGPOS_{y,t}^{T} = \beta_{y,0}^{TPOS} + \beta_{y,1}^{TPOS} \log\left(TVAD_{y,t}^{T}\right) + \beta_{y,2}^{TPOS} \log\left(NEWSPOS_{y,t-1}^{T}\right)$$
$$+\beta_{y,3}^{TPOS} \log\left(NEWSNEG_{y,t-1}^{T}\right) + \beta_{y,4}^{TPOS} BREADPOS_{y,t}^{T}$$
$$+\beta_{y,5}^{TPOS} MON + \cdots + \beta_{y,10}^{TPOS} SAT + \varepsilon_{y,t}^{TPOS}$$

(4) $$BLOGNEG_{y,t}^{T} = \beta_{y,0}^{TNEG} + \beta_{y,1}^{TNEG} \log\left(TVAD_{y,t}^{T}\right) + \beta_{y,2}^{TNEG} \log\left(NEWSPOS_{y,t-1}^{T}\right)$$
$$+\beta_{y,3}^{TNEG} \log\left(NEWSNEG_{y,t-1}^{T}\right) + \beta_{y,4}^{TNEG} BREADPOS_{y,t}^{T}$$
$$+\beta_{y,5}^{TNEG} MON + \cdots + \beta_{y,10}^{TNEG} SAT + \varepsilon_{y,t}^{TNEG}$$

$BLOGPOS_{y,t}$ and $BLOGNEG_{y,t}$ are the share of positive and negative blog postings in year *y* and on day *t.* Superscripts *P* and *T* are for Firms P and T, respectively. These variables represent consumer sentiments about Firms P and T. We use sentiment shares instead of positive and negative counts to account for the potential effect of the blog posting volume, which tends to increase over the observation period. *TVAD* is TV advertising spending. $NEWSPOS_{y,t-1}$ and $NEWSNEG_{y,t-1}$ are the volume of positive and negative news and represent the sentiment of news media about the firms on the previous day. We use the volume of news sentiment because sentiment volume can carry meaningful information. This is consistent with previous studies (e.g., Burmester et al. 2015; Stephen and Galak 2012). To control for product quality of each company, we include the share of positive blog postings about bread-related topics ($BREADPOS_{y,t}$) extracted from topic modeling which is explained in the data section. We do not include negative sentiment share due to collinearity. There are hardly any negative sentiments about bread-related topics. *MON* - *SAT* are the day of the week dummies to control for day-specific fixed effects.

While consumer sentiments about the firms can be affected by the sentiment expressed in the news media, the latter can be also affected by the former (Stephen and Galak 2012). To deal with potential endogeneity due to the reverse causality, we use lagged sentiments expressed in

news media ($NEWSPOS^{P}_{y,t-1}, NEWSNEG^{P}_{y,t-1}, NEWSPOS^{T}_{y,t-1},\ NEWSNEG^{T}_{y,t-1}$) by one period (day). We do not lag TV advertising and product quality because there is no issue of reverse causality for these variables. That is, it is not feasible to adjust TV advertising or product quality in a short time period. Finally, we use log-transformed values for TV advertising and news sentiment volume due to their skewed distributions.

Data and Measurement

Pseudo-product-harm crisis

We introduce a pseudo-product-harm crisis case that involved two competing firms. On December 23, 2010, a middle-aged man, later known as a franchise owner of Firm T, posted a picture of a loaf of bread with a rotten rat in it on a famous Korean blog site. He claimed that he bought the bread from a franchise store of Firm P near his home. The immediate responses from the public were like those in a typical product harm crisis. That is, people criticized Firm P for this awful product defect. But on December 31, news media revealed that the franchise owner of Firm T had his son purchase the bread from the Firm P's store, then put the rat in the bread to ruin the sales of the competing store. Although the crisis period was only eight days, sales of both companies during the Christmas season dropped significantly by an estimated 17–18% compared with the previous year (Chosun Ilbo 2011). The Christmas season is important because more than 30% of the annual sales of the Korean bakery industry occur during this season.

Firm P was the victim firm though it was initially considered the offending firm, thus it was a pseudo-product-harm crisis to Firm P. Firm T was the actual offending firm as its franchise owner caused the problem. Firm T did not immediately admit its responsibility or take appropriate action to resolve the issue.

Data

We gathered the two firms' daily advertising data from January 2009 to December 2011 from a large marketing research company in South Korea. Firm P is the largest and Firm T is the second largest firm in the Korean bakery industry, with sales of $2.32 billion and $0.53 billion, respectively, in 2012. Advertising spending in this industry is highly concentrated during the fourth quarter each year. Figure 1 shows daily TV advertising spending of the two firms during the fourth quarters of the focal years.

==Figure 1 about here==

From one of the largest portal sites in Korea, we collected consumer-generated blog posts (68,800 for Firm P and 51,443 for Firm T) and online news media articles (9,235 for Firm P and 5,806 for Firm T) between January 2009 and December 2011. Given that these blogs and news articles are in unstructured free-text format, we leverage text-mining approaches to construct the variables for empirical analysis. Namely, we apply topic modeling (Blei, Ng, and Jordan 2003) to capture the underlying topics associated with blog posts and news articles. We also measure the sentiment of each blog post and news article based on positive and negative keywords (Hu and Liu 2004). Table 1 shows the variables, their definitions and descriptive statistics.

==Table 1 about here==

Measure of consumer sentiment: Sentiment analysis

Social media is a great resource to detect consumer sentiment. In our analysis, we investigate how advertising affects consumer's sentiment on each firm. While there are numerous studies that use sentiment analysis on documents written in English, relatively little work has been done on non-English languages. Since our focal firms are based in Korea, the

social media contents are also written in the Korean language. We leverage OpenHangul project[2] to conduct sentiment analysis on Korean blog posts and news articles (An and Kim 2015). We note that the method used in OpenHangul is similar to that of English sentiment analysis. Specifically, An and Kim (2015) construct a sentiment lexicon database using a crowdsourcing method by asking people to label each Korean word as neutral, positive, or negative. The project provides a web-based API that enables us to extract keyword- and document-level sentiments from our blog posts and news articles.

We use the Korean language sentiment lexicon database of 517,178 words from the project. For each article, we count the occurrences of positive and negative keywords, then calculate the overall sentiment by subtracting the negative score from the positive score (e.g., Archak, Ghose, and Ipeirotis 2011; Das and Chen 2007). If a post's positive score is greater (smaller) than its negative score, the post is classified as a positive (negative) post; if a post has the same number of positive and negative scores, it is classified as neutral. We then calculate the share of positive, neutral, and negative posts on each day by dividing the number of positive, neutral, and negative posts by the total number of posts on that day. Figure 2 shows the daily share of blog posts for Firms P and T. Firm T's positive shares show higher variance than Firm P's.

==Figure 2 about here==

The sentiments of news articles are calculated in a similar manner. Figure 3 shows the daily number of positive and negative news articles about Firms P and T. We observe a big increase in negative news volume for both firms during the crisis (2010).

==Figure 3 about here==

[2] openhangul.com/

Measure of product quality perception: Topic modeling and sentiment analysis

To properly estimate the effect of advertising and news coverage on consumer sentiment, it is important to control for product quality of the firms. We extract the consumer-perceived product quality from blogs and news media articles through topic modeling and sentiment analysis on the extracted topics.

Blog postings and news articles cover various topics related to our focal companies such as new product releases, comparison of their products, franchise consulting, loyalty programs, and complaints about products. Thus, the first step is to extract various underlying topics from the text collections. Topic models, introduced in the computer science literature, tackle this problem. Among various topic model algorithms, Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003) is the most representative algorithm that has been successfully adopted in the management literature (e.g., Shi, Lee, and Whinston 2016; Tirunillai and Tellis 2014). The strength of LDA is that it is an unsupervised machine learning technique, which does not require a manual classification of the data. The underlying assumption of LDA is that a collection of documents is generated by latent topics and that each topic is a distribution over a set of keywords (or vocabulary). It is also assumed that a specific document is an instantiation of a handful of those topics. By observing a large collection of documents, overall and document-specific topic distributions can be jointly estimated.

For our analysis, we build two topic models: one for Firm P and the other for Firm T. The reason to build two separate models is to capture distinct topics for each firm. Firm P's topic model is estimated from 78,035 documents (including both blog posts and news articles) and Firm T's topic model is generated from 57,249 documents. The parameter researchers should specify in topic model estimation is the number of topics. We vary the number (10, 20, 30, 50,

100, 150, and 200) to find that a 100-topic model gives the most accurate results in terms of perplexity score as well as human interpretation. To illustrate the LDA results, we show ten representative topics for each topic model in Table 2.

==Table 2 about here==

Note that a topic is a probabilistic distribution over all the keywords in the text corpus and that we only show the top five keywords based on the associated weights. We observe that blog posts and news articles cover various topics: the rat-bread event (the focus of this article), special events (e.g., Christmas and Valentine's day), products (e.g., bread, cake, croissant, and ice cream), franchise, and loyalty programs. The topics generated from Firms P's and T's blog postings and news articles are comparable even though we created separate topics for each firm.

To filter blog posts and news articles related to product quality, we leverage the results from the LDA topic models. We first identify topics related to product quality for each firm. These topics are about bread and cake, which include 11 sub-topics for Firms P and T. Then, we construct subsamples consisting of blog posts that have at least 70% in the product quality related topics. We measure the daily sentiment share from those product quality-related samples. Figure 4 shows the daily share of positive posts about bread and cakes of Firms P and T.

==Figure 4 about here==

Results

Table 3 shows the estimation results. First, advertising is not significantly associated with consumers' positive or negative sentiment share for Firm P in all periods. However, advertising is negatively related to Firm T's consumer sentiment during (2010) and after the crisis (2011). That is, higher advertising spending is associated with a lower share of positive sentiment. This

is an interesting result. It is probably because advertising reminds consumers of the negative emotion related to the rat-bread event or because consumers' confidence in the firm's claim in the advertising message decreased. This result is consistent with prior studies. For example, Zhao, Zhao, and Helsen (2011) find the effectiveness of advertising significantly decreases during a product-harm crisis. Firms also seem to understand this point. They report that Kraft either significantly decreased its advertising amount or did not spend any amount on advertising of the affected brands during the product harm crisis. According to Williams and Buttle (2014), marketing managers think that it is better to remain silent at times of crisis and often pull scheduled advertising due to the concern that media expenditure to counteract negative word-of-mouth might achieve the opposite. This result remains significant even after the event (2011). Higher advertising is related to a higher share of negative consumer sentiment. For Firm T, advertising not only decreases the share of positive sentiment, but also increases the share of negative sentiment.

== Table 3 about here==

Second, the volume of negative sentiment news articles is associated with a lower positive sentiment share and a higher negative sentiment share during the event (2010). These results are possibly because Firm P was initially misunderstood as the cause of the problem. Given that consumer sentiment is an important determinant of firms' sales and profitability, a pseudo-product-harm crisis can inflict harm to the victim firm. However, this negative effect disappeared after the crisis (2011), therefore a pseudo-crisis is not likely to leave a long-term damage to the firms unless the negative event lasts a long time. The effects of news publicity are similar to Firm T. The negative sentiment news volume increases the negative sentiment share and the positive news volume reduces the negative sentiment share during (2010) the crisis.

Given the significantly larger amounts of negative news publicity during the crisis (see Figure 3) than other periods, both firms' reputations (represented by consumer sentiment) are materially damaged.

Implications, Limitations, and Future Research

We investigate the effect of paid media (advertising) and earned media (news publicity) on consumer sentiment expressed in social media surrounding a pseudo product harm crisis. This study contributes to the study of product harm crises by broadening our perspective to a special case of crises that firms face, i.e., a pseudo-product-harm crisis. Our findings provide important implications on the management of pseudo-product-harm crisis. First, the victim firm should focus on building appropriate public relations and news media strategies to mitigate the effect of negative news publicity instead of advertising during a pseudo-product-harm crisis. During the crisis, the amount of negative news significantly increases, which in turn negatively affects consumer sentiment. On the other hand, advertising does not affect consumer sentiment. However, the fact that the negative effect of bad news does not last beyond the crisis period gives a consolation to the victim firm. Once the truth is revealed, negative news abates and does not affect consumer sentiment any more.

How should the offending firm respond to the pseudo-product-harm crisis when the crisis is initially caused by the inappropriate action of a franchisee? First, the offending firm should act promptly to minimize any consumer backlash even if the crisis was not caused by the firm's management. In our example, the offending firm thought doing nothing was the best response to the crisis. However, customers wanted a responsible action from the firm and criticized the firm's initial inaction. This mismanagement of the crisis by the firm led to massive negative

consumer sentiment as well as declining advertising effectiveness. Thus, firms need to carefully monitor and manage any crisis caused by their stakeholders including franchisees. Second, the offending firm is also advised to focus on formulating a sound news media strategy to reduce negative news publicity. Advertising spending surrounding a pseudo-product-harm crisis can backfire and exacerbate the crisis.

Overall, our analysis suggests that while both offending and victim firms suffer from the crisis, the offending firm suffers more in terms of advertising effectiveness and negative news publicity. Adverse rumors and false claims about competitors can often be effective in politics during election campaigns which last only a short period of time. However, the time horizon of business is much longer and maintaining a long-term perspective is critical. Thus, apart from ethical concern, those negative tactics which can lead to a pseudo-product-harm crisis in business do not seem to be an effective strategy to increase firm performance.

A few limitations in our study provide avenues for future research. First, while consumer sentiment is an important determinant of firm performance, due to the unavailability of data, we could not link the effect of the crisis on the firms' sales or profits. Future studies can extend our study to incorporate those performance metrics in a pseudo-product-harm crisis. Second, our study provides managerial insights on pseudo-product-harm crisis management caused by a firm's stakeholders such as franchisees. While our analysis reveals an interesting result that the offending firm seriously suffers from this type of pseudo-product-harm crisis, future studies need to look into whether the negative effects on the offending firm are similar or worse when the crisis is caused by the management of the offending firm. Third, we have examined only one pseudo-product-harm crisis. While it is difficult to collect data across a large number of pseudo-

crisis cases, it will be meaningful to extend our study into other cases to test the generalizability of our findings.

References

A.C. Nielsen (2012), "Report on Global Trust in Advertising and Brand Messages," [www.fi.nielsen.com/site/documents/NielsenTrustinAdvertisingGlobalReportApril2012.pdf].

Ahluwalia, Rohini (2002), "How Prevalent Is the Negativity Effect in Consumer Environments?" *Journal of Consumer Research*, 29 (2), 270-279.

Ahluwalia, Rohini, Robert E. Burnkrant, and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Marketing Research*, 38 (May), 203–214.

An, Jungkook and Hee-Woong Kim (2015), "Building a Korean Sentiment Lexicon Using Collective Intelligence," *Journal of Intelligence and Information Systems*, 21(2) 49-67.

Archak, Nikolay, Anindya Ghose, and Panagiotis G. Ipeirotis (2011), "Deriving the Pricing Power of Product Features by Mining Consumer Reviews," *Management Science*, 57 (8), 1485–1509.

Berger, Jonah, Alan T. Sorensen, and Scott J. Rasmussen (2010), "Positive Effects of Negative Publicity: When Negative Reviews Increase Sales," *Marketing Science*, 29 (5), 815–827.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan (2003), "Latent Dirichlet Allocation," *Journal of Machine Learning Research*, 3, 993-1022.

Borah, Abhishek and Gerard J. Tellis (2016), "Halo (Spillover) Effects in Social Media: Do Product Recalls of One Brand Hurt or Help Rival Brands?" *Journal of Marketing Research*, 53 (April), 143-160.

Bruce, Norris I., Natasha Zhang Foutz, and Ceren Kolsarici (2012), "Dynamic Effectiveness of Advertising and Word-of-Mouth in the Sequential Distribution of Short Life Cycle Products," *Journal of Marketing Research*, 49 (August), 435–51.

Burmester, Alexa B., Jan U. Becker, Harald J. van Heerde, and Michel Clement (2015), "The Impact of Pre- and Post-Launch Publicity and Advertising on New Product Sales," *International Journal of Research in Marketing*, 32 (4), 408-417.

Business Insider (2010), "BP's Apologetic Ad Campaign Is Just One More Dumb PR Decision," June 3, [www.businessinsider.com/bps-new-ad-campaign-just-one-more-dumb-pr-decision-2010-6].

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), 214-226.

Chevalier, Judith A. and Dina Mayzlin (2006), "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research*, 43 (3), 345-354.

Chosun Ilbo (2011), "Blown-off Christmas Sales of All Bakeries Due to the 'Rat Bread' Crisis that Intended to Reduce Competitors' Sales," (January 1), [news.chosun.com/site/data/html_dir/2010/12/31/2010123101675.html].

Cleeren, Kathleen, Harald J. van Heerde, and Marnik G. Dekimpe (2013), "Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises," *Journal of Marketing*, 77 (March), 58-77.

Clemons, Erik K., Guodong Gordon Gao, Lorin M. Hitt (2006), "When Online Reviews Meet Hyper Differentiation: A Study of the Craft Beer Industry," *Journal of Management Information Systems*, 23 (2), 149-171.

Cowden, Kimberly and Timothy L. Sellnow (2002) "Issues Advertising as Crisis Communication: Northwest Airlines' Use of Image Restoration Strategies During the 1998 Pilot's Strike," *International Journal of Business Communication*, 39 (2), 193-219.

Darke, Peter R. and Robin J.B. Ritchie (2007), "The Defensive Consumer: Advertising Deception, Defensive Processing, and Distrust," *Journal of Marketing Research*, 44 (1), 114-127.

Das and Chen (2007), "Yahoo! for Amazon: Sentiment Extraction from Small Talk On The Web," *Management Science*, 53 (9), 1375–1388.

Dawar, Niraj and Madan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 38 (May), 215–226.

Dellarocas, Chrysanthos, Xiaoquan 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.

Divol, Roxane, David Edelman, and Hugo Sarrazin (2012), "Demystifying Social Media," *McKinsey Quarterly*, (April 2012), [www.mckinsey.com/insights/marketing_sales/demystifying_social_media].

Duan, Wenjing, Bin Gu, and Andrew B. Whinston (2008), "The Dynamics of Online Word-of-Mouth and Product Sales: An Empirical Investigation of the Movie Industry," *Journal of Retailing* 84 (2), 233-242.

Financial Times (2005) "Food Chain 'Thrilled' by Arrest of Woman Who Said She Found a Finger in Her Chili," (April), [www.ft.com/intl/cms/s/0/d4fd0682-b393-11d9-ad2b-00000e2511c8.html#axzz3C0dlau4W].

Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word-Of-Mouth Communication," *Marketing Science*, 23 (4), 545-560.

Goes, Paulo B., Mingfeng Lin, and Ching-man Au Yeung (2014), "Popularity Effect in User-Generated Content: Evidence from Online Product Reviews," *Information Systems Research*, 25 (2), 222-238.

Goh, Khim-Yong, Cheng-Suang Heng, Zhijie Lin. (2013), "Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content," *Information Systems Research*, 24 (1), 88-107 .

Griffiths, Thomas L. and Mark Steyvers (2004), "Finding Scientific Topics," Proceedings of the National Academy of Sciences, 5228-5235.

Herr, Paul M., Frank R. Kardes, and John Kim (1991), "Effects of Word-of-Mouth and Product-Attribute Information of Persuasion: An Accessibility-Diagnosticity Perspective," *Journal of Consumer Research*, 174, 454-462.

Hu, Minqing and Bing Liu (2004), "Mining and summarizing customer reviews," Proceedings of 10th ACM SIGKDD International Conference Knowledge Discovery and Data Mining (KDD-2004), Association for Computing Machinery, New York, 168-177.

Kim, Ho and Dominique M. Hanssens (2016), "Advertising and Word-of-Mouth Effects on Pre-Launch Consumer Interest and Initial Sales of Experience Products," *Journal of Interactive Marketing*, forthcoming.

Kim, Sojung and Sejung Choi (2014), "Is Corporate Advertising Effective in a Crisis? The Effects of Crisis Type and Evaluative Tone of News Coverage," *Journal of Promotion Management*, 20 (2), 97-114.

Kwark, Young, Gene Moo Lee, Paul A. Pavlou, and Liangfei Qiu (2016), "The Spillover Effects of User-Generated Online Product Reviews on Purchases: Evidence from Clickstream Data," *Proceedings of International Conference on Information Systems*, Forthcoming.

Lu, Xianghua, Sulin Ba, Lihua Huang, and Yue Feng (2013), "Promotional Marketing or Word-Of-Mouth? Evidence from Online Restaurant Reviews," *Information Systems Research*, 24 (3) 596-612.

Luca, Michael (2011), "Reviews, Reputation, and Revenue: The Case of Yelp.com," Harvard Business School Working Paper, No. 12-016, September.

Luo, Xueming and C.B. Bhattacharya (2009), "The Debate over Doing Good: Corporate Social Performance, Strategic Marketing Levers, and Firm-Idiosyncratic Risk," *Journal of Marketing*, 73 (6), 198-213.

Luo, Xueming, Jie Zhang, and Wenjing Duan (2013) "Social Media and Firm Equity Value," *Information Systems Research*, 24 (1), 146–163.

Maeil Business Newspaper (2011), "Why Did 70 stores of CJ Tous Les Jours Go out of Business?" (April 12), [news.mk.co.kr/v3/view.php?year=2011&no=232188].

Meyer, Jeffrey, Reo Song, and Kyeongnam Ha (2016), "The Effect of Product Placements on the Evaluation of Movies," *European Journal of Marketing*, 50 (3).

New York Times (2007), "Confronting Ghosts of 2000 in South Carolina," (October 19), [www.nytimes.com/2007/10/19/us/politics/19mccain.html?_r=0].

Onishi, Hiroshi and Puneet Manchanda (2012), "Marketing Activity, Blogging and Sales," *International Journal of Research in Marketing*, 29, 221-234.

Porter, Michael E. and Mark R. Kramer (2011), "Creating Shared Value," *Harvard Business Review*, January–February, 1-17.

Riquelme, Isabel P., Sergio Román, and Dawn Iacobucci (2016), "Consumers' Perceptions of Online and Offline Retailer Deception: A Moderated Mediation Analysis," *Journal of Interactive Marketing*, 35, 16–26.

Rishika, Rishika, Ashish Kumar, Ramkumar Janakiraman, and Ram Bezawada (2013), "The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation," *Information Systems Research*, 24 (1), 108-127.

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), 366–373.

Ross, Alec (2016), *The Industries of the Future*, Simon & Schuster.

Sentinel Projects (2010), "Turn a PR Crisis into Positive Online Buzz: Lessons from The Gap," October 13, [www.sentinel-projects.com/blog/2010/10/turn-a-pr-crisis-into-positive-online-buzz-lessons-from-the-gap].

Shi, Zhan, Gene Moo Lee, and Andrew B. Whinston (2016), "Towards a Better Measure of Business Proximity: Topic Modeling for Industry Intelligence," *MIS Quarterly*, Forthcoming.

Simonson, Itamar and Emanuel Rosen (2014), "What Marketers Misunderstand about Online Reviews," *Harvard Business Review*, January–February.

Sissors, Jack Z. and Roger B. Baron (2010), *Advertising Media Planning*, 7th ed., McGraw-Hill Education.

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 (5), 624-639.

The Atlantic (2013), "The Simple Reason Why Goodreads Is So Valuable to Amazon," [www.theatlantic.com/business/archive/2013/04/the-simple-reason-why-goodreads-is-so-valuable-to-amazon/274548].

The Wall Street Journal (2010), "BP Tripled Its Ad Budget After Oil Spill," September 1 [www.wsj.com/articles/SB10001424052748703882304575465683723697708].

The Wall Street Journal (2014), "Companies Turn to Social-Media Coaches," March 26 [www.wsj.com/articles/SB10001424052702303949704579461412963008056].

The Wall Street Journal (2015), "KFC Sues Chinese Companies Over Alleged Eight-Legged Chicken Rumors," (June 1) [www.wsj.com/articles/kfc-sues-chinese-companies-over-alleged-eight-legged-chicken-rumors-1433166317].

Tipton, Martha Myslinski, Sundar G. Bharadwaj, Diana C. Robertson (2009), "Regulatory Exposure of Deceptive Marketing and Its Impact on Firm Value," *Journal of Marketing,* 73 (6), 227-243.

Tirunillai, Seshadri, and Gerard J. Tellis (2014), "Mining Marketing Meaning From Online Chatter: Strategic Brand Analysis of Big Data Using Latent Dirichlet Allocation," *Journal of Marketing Research*, 51 (4), 463-479.

Trusov, Michael, Randolph 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.

Tybout, Alice M., Bobby J. Calder, and Brian Sternthal (1981), "Using Information Processing Theory to Design Marketing Strategies," *Journal of Marketing Research*, 18 (1), 73-79.

Van Heerde, Harald J., Els Gijsbrechts, and Koen Pauwels (2015), "Fanning the Flames? How Media Coverage of a Price War Affects Retailers, Consumers, and Investors," *Journal of Marketing Research*, 52 (5), 674-693.

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

Vanity Fair (2004), "The Trashing of John McCain," (November) [www.vanityfair.com/news/2004/11/mccain200411].

Villanueva, Julian, Shijin Yoo, and Dominique M. Hanssens (2008), "The Impact of Marketing-Induced Versus Word-of- Mouth Customer Acquisition on Customer Equity Growth," *Journal of Marketing Research*, 45 (February), 48–59.

Wagner, Tillmann, Richard J. Lutz, and Barton A. Weitz (2009), "Corporate Hypocrisy: Overcoming the Threat of Inconsistent Corporate Social Responsibility Perceptions," *Journal of Marketing*, 73 (6), 77-91.

Williams, Martin and Francis Buttle (2014). "Managing Negative Word-of-Mouth: An Exploratory Study," *Journal of Marketing Management*, 30 (13-14), 1423-1447.

Zhao, Yi, Ying Zhao, and Kristiaan Helsen (2011), "Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics After a Product-Harm Crisis," *Journal of Marketing Research*, 48(April), 255-267.

Table 1. Descriptive Statistics

	Description	Min	Max	Mean	Std. dev.
	Dependent Variable				
$BLOGPOS_{y,t}^{P}$	Share of positive blog posts	0.000	1.000	0.804	0.127
$BLOGNEG_{y,t}^{P}$	Share of negative blog posts	0.000	1.000	0.094	0.106
$BLOGPOS_{y,t}^{T}$	Share of positive blog posts	0.000	1.000	0.720	0.231
$BLOGNEG_{y,t}^{T}$	Share of negative blog posts	0.000	1.000	0.077	0.107
	Independent Variables				
$TVAD_{y,t}^{P}$	Television advertising spending	0.000	$157423.000	$28153.710	$32100.480
$NEWSPOS_{y,t}^{P}$	Number of positive news articles	0.000	71.000	6.645	9.143
$NEWSNEG_{y,t}^{P}$	Number of negative news articles	0.000	55.000	0.685	3.596
$BREADPOS_{y,t}^{P}$	Share of positive blog posts about bread-related topics	0.000	0.167	0.021	0.033
$TVAD_{y,t}^{T}$	Television advertising spending	0.000	$146262.000	$17167.920	$29015.240
$NEWSPOS_{y,t}^{T}$	Number of positive news articles	0.000	54.000	3.725	6.337
$NEWSNEG_{y,t}^{T}$	Number of negative news articles	0.000	49.000	0.438	3.151
$BREADPOS_{y,t}^{T}$	Share of positive blog posts about bread-related topics	0.000	0.400	0.021	0.045

N = 276. Only the fourth quarters of each year are included. Subscript *P* is for Firm P and *T* is for Firm T. *y* is year and *t* is day.

Table 2. Ten Example Topics from a 100-Topic Model of Blog Posts and News Articles

Firm	Topic	Top Ten keywords
Firm P	1	rat-bread, Mr. Kim[3], photo, Internet, police
	2	Christmas, cake, December, secret, present
	3	chocolate, Valentine's day, white day[4], economical, Pepero[5]
	4	cake, birthday, birthday party, firm P, mom
	5	cake, cream, soft, blueberry, cheesecake
	6	bakery, macaroon, tart, croissant, dessert
	7	ice cream, cool, bean, ice, fruit
	8	our wheat, price, powder, firm P's group, product
	9	service, analysis, consulting, free, possible
	10	gift, event, points, gift card, culture gift card
Firm T	1	Firm P, rat bread, Mr. Kim, Internet, photo
	2	Christmas, cake, December, Firm T, Pororo[6]
	3	chocolate, Valentine's day, white day, sweet, special
	4	mom, cake, dad, birthday, Firm T, birthday party
	5	cream, cake, cheesecake, blueberry, sweet potato
	6	bakery, famous, made, Firm T, Firm P
	7	blog, ice cream, dessert, yogurt, blueberry
	8	our wheat, bagel, corn, bakery, drama
	9	consultant, possible, analysis, fee, food court
	10	gift, gift card, cosmetic, Coffee Franchise, points

[3] Mr. Kim is the person who put the rat in the firm P's bread.
[4] White Day is March 14, one month after Valentine's Day. It is marked in Southeast Asian countries such as Japan, Korea, Taiwan, and China. In these countries, women present gifts to men on Valentine's Day. On White Day, men who received gifts on Valentine's Day return the favor to women.
[5] Pepero is a cookie stick, dipped in compound chocolate, manufactured by a large Korean company.
[6] Pororo is a Korean computer-animated cartoon series for kids.

Table 3. Effects of TV Advertising and News Sentiment on Consumer Sentiment
(Standard errors in parenthesis)

Dependent variable	Independent variable	2009 (10/1 ~ 12/31)	2010 (10/1 ~ 12/22)	2011 (10/1 ~ 12/31)
Positive blog share of Firm P ($BLOGPOS_{y,t}^{P}$)	$TVAD_{y,t}^{P}$	-0.0031	0.0014	0.0023
		(0.0029)	(0.0015)	(0.0040)
	$NEWSPOS_{y,t-1}^{P}$	-0.0082	0.0004	-0.0007
		(0.0138)	(0.0116)	(0.0161)
	$NEWSNEG_{y,t-1}^{P}$	0.0522	-0.0374***	0.0413*
		(0.0318)	(0.0119)	(0.0238)
	$BREADPOS_{y,t}^{P}$	0.1454	-0.3858	-0.3223
		(0.4138)	(0.3515)	(0.6727)
Negative blog share of Firm P ($BLOGNEG_{y,t}^{P}$)	$TVAD_{y,t}^{P}$	0.0016	-0.0017	0.0006
		(0.0020)	(0.0012)	(0.0040)
	$NEWSPOS_{y,t-1}^{P}$	0.0029	0.0054	-0.0106
		(0.0114)	(0.0094)	(0.0040)
	$NEWSNEG_{y,t-1}^{P}$	-0.0055	0.0299**	-0.0328
		(0.0181)	(0.0128)	(0.0202)
	$BREADPOS_{y,t}^{P}$	-0.3152	0.4245	-0.3025
		(0.2366)	(0.2973)	(0.3490)
Positive blog share of Firm T ($BLOGPOS_{y,t}^{T}$)	$TVAD_{y,t}^{T}$	-0.0044	-0.0205***	-0.0307***
		(0.0063)	(0.0059)	(0.0056)
	$NEWSPOS_{y,t-1}^{T}$	-0.0548*	-0.0648*	0.0179
		(0.0311)	(0.0333)	(0.0261)
	$NEWSNEG_{y,t-1}^{T}$	0.0598	0.0004	-0.0091
		(0.1092)	(0.0487)	(0.0305)
	$BREADPOS_{y,t}^{T}$	-0.0852	0.0699	-0.0976
		(0.2345)	(0.4645)	(0.2227)
Negative blog share of Firm T ($BLOGNEG_{y,t}^{T}$)	$TVAD_{y,t}^{T}$	-0.0030	-0.0012	0.0078***
		(0.0031)	(0.0014)	(0.0028)
	$NEWSPOS_{y,t-1}^{T}$	-0.0229*	-0.0156**	-0.0037
		(0.0127)	(0.0071)	(0.0126)
	$NEWSNEG_{y,t-1}^{T}$	-0.0430	0.0343**	-0.0133
		(0.2943)	(0.0152)	(0.0204)
	$BREADPOS_{y,t}^{T}$	0.3469***	0.1633	0.0302
		(0.1537)	(0.2238)	(0.3013)

Note: Estimates of weekdays are omitted to avoid clutter.

Figure 1. Daily TV Advertising Spending (Unit: $)

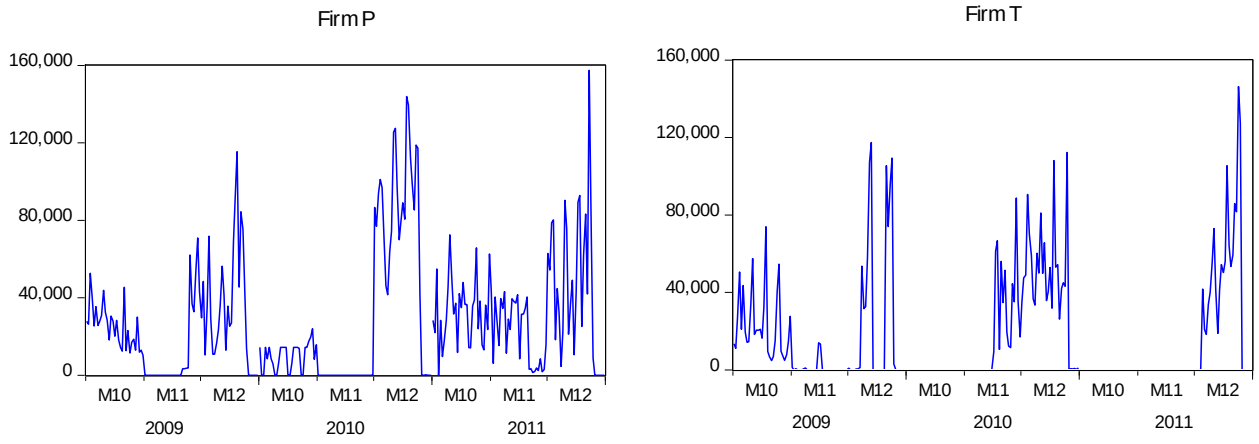


Figure 2. Daily Share of Positive and Negative Blog Posts

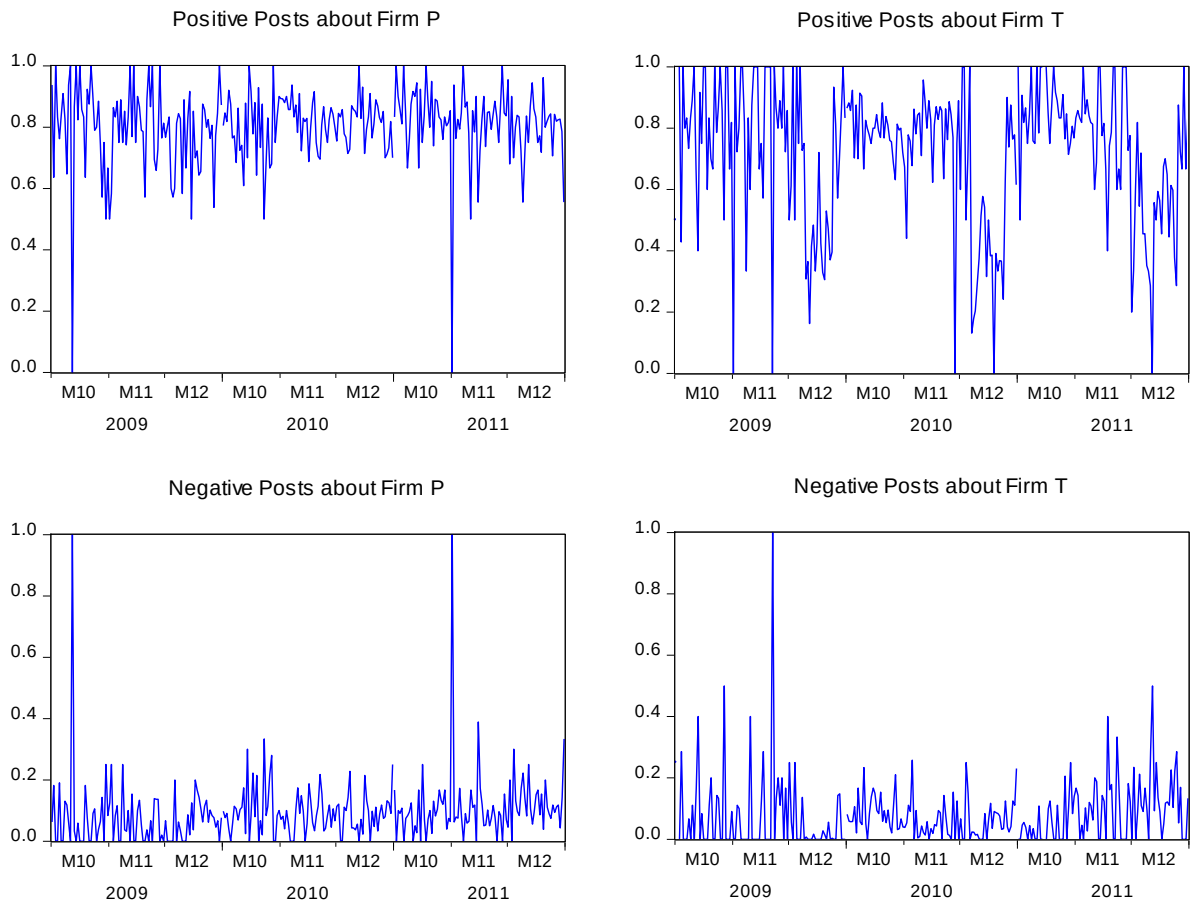


Figure 3. Daily Number of Positive and Negative News Articles

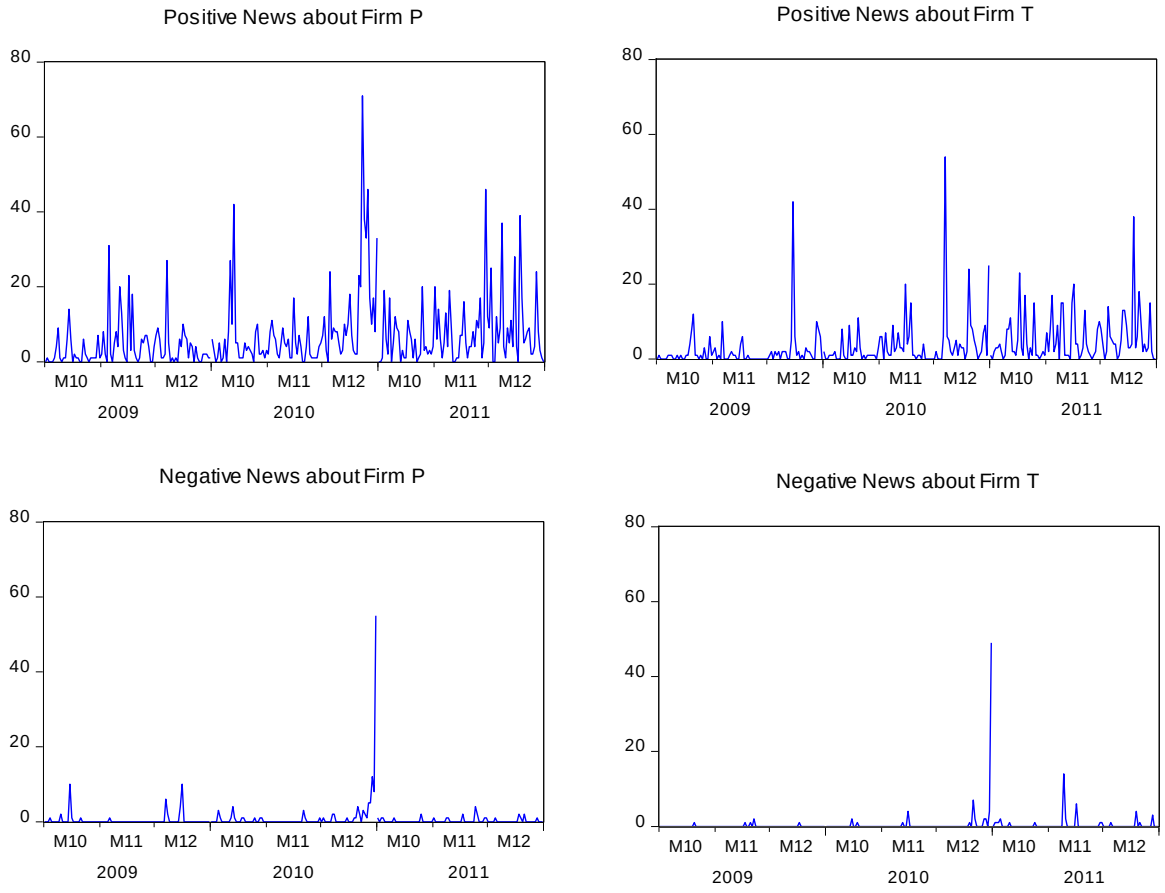
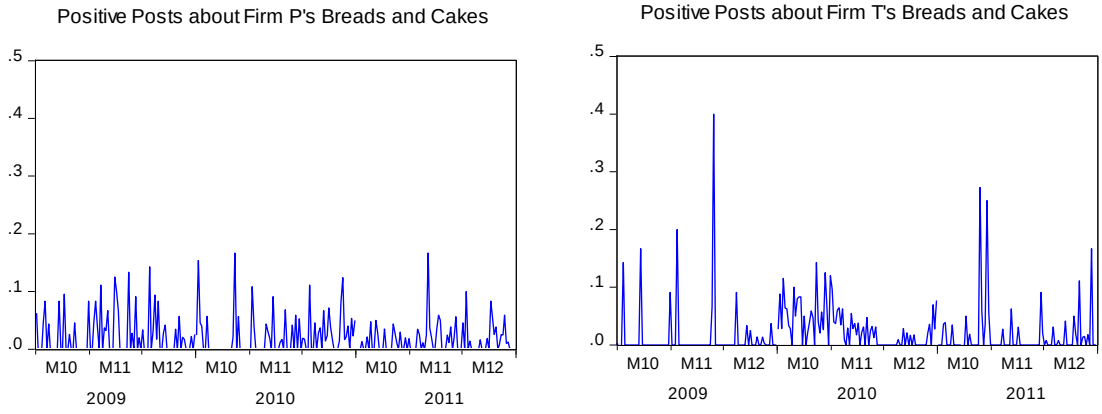


Figure 4. Daily Share of Positive and Negative Blog Posts about Bread-Related Topics



Appendix. Latent Dirichlet Allocation (LDA) Topic Modeling Algorithm

Here, we formally describe the LDA's mathematical procedure. Let *D* be the number of input documents (blog posts and news articles in our case) to the algorithm, where each document d is a collection of words $\{w_n^d | n = 1, 2, \ldots, N^d\}$. LDA treats a document as a bag of words without considering the relative ordering of the words. Then, let *K* be the number of latent topics that generated the input documents. Each topic k is a probabilistic distribution (φ^k) over the whole vocabulary (i.e., the set of distinct words in the whole input document corpus), where φ_w^k is the probability of word *w* in topic *k*. It is assumed that each document *d* is generated over a probabilistic distribution (θ^d) over *K* topics, where θ_k^d is the topic proportion for topic *k* in document *d*. Lastly, assume that z_n^d is the topic assignment of the nth word in document *d*. Given φ^k (per-topic distribution over keywords) and θ^d (per-document distribution over topics), the probability of observing document *d* is:

$$\prod_{n=1}^{N^d} \left(\sum_{k=1}^{K} P(w_n^d | z_n^d = k, \theta^k)\, P(z_n^d = k | \theta^d) \right) = \prod_{n=1}^{N^d} \left(\sum_{k=1}^{K} \varphi_{w_n^d}^k\, \theta_k^d \right)$$

where the term inside the product operator is the probability of the nth word in document being w_n^d. LDA further assumes θ and φ are drawn from Dirichlet priors with hyperparameters α and β, respectively. Having observed the input documents, *w*, we have the posterior distribution:

$$P(z, \theta, \varphi | \alpha, \beta) = \frac{P(w, z, \theta, \varphi | \alpha, \beta)}{P(w | \alpha, \beta)}$$

Finally, we can estimate θ and φ by using a Monte Carlo procedure from Bayesian statistics and statistical physics (Griffiths and Steyvers 2004).