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

Abstract

The slandering of a firm's products by competing firms poses significant threats to the victim firm, with the resulting damage often being as harmful as that from product-harm crises. In contrast to a true product-harm crisis, however, this disparagement is based on a false claim or fake news; thus, we call it a *pseudo*-product-harm crisis. Using a pseudo-product-harm crisis event that involved two competing firms, this research examines how consumer sentiments about the two firms evolved in response to the crisis. Our analyses show that while both firms suffered, the damage to the offending firm (which spread fake news to cause the crisis) was more detrimental, in terms of advertising effectiveness and negative news publicity, than that to the victim firm (which suffered from the false claim). Our study indicates that, even apart from ethical concerns, the false claim about the victim firm was not an effective business strategy to increase the offending firm's performance.

Keywords: fake news, product-harm crisis, deceptive marketing, unethical business practice, slandering, advertising, word of mouth, social media, text mining

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Introduction

Product-harm crises are incidents created by defective or dangerous products. Product-harm crises, 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's faulty ignition switch (2015), and Volkswagen's emission scandal (2015), have not only endangered the well-being of customers (Dawar and Pillutla 2000; van Heerde, Helsen, and Dekimpe 2007), but also negatively affected company sales, advertising effectiveness, and firm value (Chen, Ganesan, and Liu 2009; Cleeren, van Heerde, and Dekimpe 2013).

In addition to product-harm crises, firms often suffer from adverse rumors initiated by consumers or competitors (Tybout, Calder, and Sternthal 1981). To distinguish attacks by means of false rumors or fake news from real product-harm crises, we have dubbed the former *pseudo*-product-harm crises. 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 in San Jose, California. Although the claim later turned out to be false and led to the woman being arrested a month later for attempted grand larceny, the controversy led Wendy's stock price to drop nearly 10% and caused franchise sales in the San Francisco Bay area to fall by nearly 30% (*Financial Times* 2005). As another example, in June 2015, KFC sued three Chinese companies for spreading rumors through social media that its chickens had eight legs, seeking from each company compensation of up to 1.5 million yuan (about $245,000), an apology, and an end to these alleged practices of misinformation (*The Wall Street Journal* 2015).

When initiated by a competitor, a pseudo-product-harm crisis involves two firms, i.e., the offending firm that spreads fake news to cause the crisis and the victim firm that suffers from the false claim. Understanding the consequences of a pseudo-product-harm crisis caused by a competing firm's deceptive marketing tactics has important implications for both management strategy and business ethics. In addition, understanding the consequences of adverse rumors has become critical in a contemporary environment where social media provide a platform for information, whether real or fake, to spread with unprecedented speed and on a massive scale. With the advancement of information technology, including news apps and software bots capable of creating fake news, we increasingly witness false rumors and their devastating effects. For example, in December 2016, after a conspiracy theory spread across social media that Hillary Clinton and her campaign chief were running a child sex trafficking ring from a Washington pizza shop, a man walked into the restaurant and opened fire (the incident was afterwards dubbed "Pizzagate"; *The Washington Post* 2016). However, research on the effects of pseudo-product-harm crises on social media has been scarce, limiting our understanding of this subject.

To extend our understanding of the consequences of deceptive marketing tactics, we examine a *pseudo*-product-harm crisis where the offending firm and victim firm were identified later. We start by exploring the following research questions: (1) How did consumers respond on social media to the adverse rumor? Specifically, what were the effects of advertising and news publicity on consumer sentiment and how did these effects evolve over time? By investigating these issues, we are able to additionally address the following related questions: (2) Did deceptive marketing[1] benefit the offending firm? Was it a gainful business strategy (apart from the ethical concerns)? (3) Did deceptive marketing damage the victim firm? If so, to what extent?

[1] There is no standard terminology for the use of adverse rumors against competitors in business. Both academicians and practitioners use deceptive marketing and negative marketing interchangeably. We use deceptive marketing throughout the paper.

To answer these questions and assess both ethical concerns and the business implications of using deceptive marketing tactics, we examine how consumer sentiment about the two competing firms, expressed in blog posts, evolved in response to the firms' advertising and news publicity before and after the pseudo-product-harm crisis. Our study utilizes both paid media (i.e., advertising) and earned media (i.e., news publicity) to examine how news publicity and firms' advertising affect consumer sentiment revealed through social media. Given the increasing importance of online word of mouth in influencing consumer purchase decisions and firm performance (Meyer, Song, and Ha 2016; Kwark et al. 2016), investigating the determinants of online consumer opinions is critical in evaluating the consequences of deceptive marketing.

We contribute to the study of business ethics by quantifying the relative impact of deceptive marketing on the offending and victim firms. The case we study is particularly appropriate for understanding the ultimate damage to the offending firm, as the identity of the offending firm in this case became publicly known shortly after the incident. In many pseudo-product-harm crises, the offenders are unknown and thus the potential losses to them cannot be measured. Therefore, by serving as a warning example to future offending firms, our research can be a valuable addition to business ethics practice.

Theoretical Background and Literature Review

In this section, we review the literature in three areas related to our specific research topics: (i) deceptive marketing, (ii) consumer sentiment and online word of mouth during crises, and (iii) advertising and news publicity during crises.

Deceptive Marketing

False claims or fake news about a firm's products by competing firms can be understood in the context of deceptive marketing and unethical business practices. Academic research has paid less attention to the consequences of deceptive marketing, both for offending and victim firms, than they have to the effects of positive marketing activities. However, understanding the effects of unethical marketing is important, given that negative information is often more salient to consumers than positive information (e.g., Ahluwalia 2002; Herr, Kardes, and Kim 1991) and that firms can easily initiate deceptive marketing on the Internet, especially through social media.

Once the truth is revealed, however, the consequences of deceptive marketing can be detrimental. Tipton, Bharadwaj, and Robertson (2009) find that the regulatory exposure of deceptive marketing negatively affects firm value even when the event carries no direct cost to the firm. In addition, the negative effects of deceptive marketing can spill over to general marketing communication and other related products, because consumers may become skeptical about the entire firm as well as the specific products involved. 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 builds on this literature by investigating whether deceptive marketing was favorable to the offending firm that employed such tactics in the specific case we examine in this article (Research question 2). This question is important because any indication that deceptive marketing is beneficial to the offending firm will create additional hurdles when trying to persuade firms to conduct their businesses ethically. However, if we find that deceptive marketing backfires and does not benefit the offending firm, then we can provide practical as well as moral grounds for encouraging firms to behave ethically. We also examine whether the victim firm suffered from the deceptive marketing and if so, how much they suffered and how long the negative effect lasted (Research question 3).

Consumer Sentiment and Online Word of Mouth

As the Internet has emerged as a leading communication platform, online word of mouth (WOM) has become a critical component of firms' marketing strategy (Divol, Edelman, and Sarrazin 2012). Research finds that online WOM is a significant determinant of product revenue (Duan, Gu, and Whinston 2008; Lu et al. 2013), profitability (Rishika et al. 2013), and firm value (Luo, Zhang, and Duan 2013). The significant effects of online WOM can be seen in various product categories, including 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 its direct impact on the focal products, online WOM can also affect the purchase of related products (e.g., substitutes and complements) in consumers' consideration sets (Kwark et al. 2016).

Studies have also shown that online WOM increasingly assumes the role of traditional marketing. Using consumer reviews on Yelp.com, Luca (2011) finds that the positive effect of online consumer reviews on restaurant demand is mostly driven by independent restaurants and that the market share of chain restaurants has declined as the influence of Yelp has increased. That is, independent restaurants with little brand reputation receive the greatest benefits from positive consumer WOM, successfully taking market shares from better-known chain restaurants whose brand reputation is already reasonably well established through traditional marketing such as advertising. Similarly, in the lodging industry, Anderson and Lawrence (2014) find that a 10% increase in a hotel's online reputation score is associated with a 9.9% increase in revenue per available room, suggesting that online reviews may influence the profitability of a firm. They also find that the influence of online reviews decreases as the hotel class level increases (e.g., midscale hotels are more affected by online reviews than upscale hotels). These findings suggest that online WOM can partially substitute for brand reputation (Simonson and Rosen 2014).

Recent research suggests that credibility and information usefulness are important determinants of WOM adoption (Hajli 2016). Once accepted, WOM has a greater impact on consumer decisions and information search than do advertising and media publicity (Goh, Heng, and Lin 2013; Kim and Hanssens 2017; Trusov, Bucklin, and Pauwels 2009). This is most likely because consumers trust WOM and recommendations from other consumers more than advertising by firms (*A.C. Nielsen* 2012; Burmester et al. 2015). Consumers tend to think of product information provided by WOM as neutral and objective in comparison to the information contained in advertising driven by profit motives. Online WOM is particularly important in a product-harm crisis situation because consumers tend to actively seek information relevant to the crisis, such as the risks of using the product. Today's online communication platforms can accelerate the spread of damage from product-harm crises. Recognizing the critical influence of social media during product-harm crises, the Consumer Product Safety Commission (CPSC) even provides a social media guide for recalling companies.[2]

In addition, online WOM generated during product-harm crises can be especially devastating as a result of negative spillover effects. The impact of WOM can be amplified during a product-harm crisis because negative information is known to be less ambiguous and more

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

diagnostic than positive information (Herr, Kardes, and Kim 1991). In the formation of judgments, consumers give greater weight to negative information than to positive information of similar intensity (Ahluwalia, Burnkrant, and Unnava 2000). In line with this reasoning, Borah and Tellis (2016) find extensive perverse spillover during automobile recalls. Negative chatter about one automobile brand increases negative chatter about another. Online chatter amplifies the negative effect of recalls on downstream sales nearly 4.5 times.

Firms can minimize these negative effects by closely monitoring consumers' online engagement in order to formulate effective response strategies for such crises. 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 Gap Inc.'s decision to scrap its new logo design and revert to the original within a week after it was faced with a scathing online backlash 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).

Therefore, understanding online WOM during a crisis is extremely important for firms when developing successful marketing strategies. Given this, our study uses blog posts as a measure of online WOM and empirically investigates the impact of advertising and news publicity on consumer sentiment surrounding the pseudo-product-harm crisis, an area not thoroughly studied by previous research (Research question 1).

Advertising and News Publicity during Crises

With the advent of social media, firms' media strategies have experienced dramatic changes. Prior studies distinguish between media types as paid (e.g., advertising) and earned media (e.g., blog posts and news articles) (Kim and Hanssens 2017; Onishi and Manchanda 2012; Stephen and Galak 2012).

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). For example, 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, in order to respond to the Deepwater Horizon oil spill (*The Wall Street Journal* 2010). Its advertising campaign largely backfired and the company faced severe criticism from consumers and environmental groups who thought BP could have better spent the money cleaning up the spill and compensating the victims (*Business Insider* 2010). Even apology advertising about recalls has harmful effects on both the recalled brand and its rivals (Borah and Tellis 2016).

Advertising strategy can be more complicated when several companies are involved in the crisis, due to competing reactions. In a pseudo-product-harm crisis, for example, the advertising strategy of the victim firm will be different from that of the offending firm. Both the victim and offending firms need to consider the competitive effects of their advertising strategy based on the actions of the other firm. Furthermore, firms involved in a crisis should take into account the reactions of competing firms that are not directly involved in the crisis. While the firms involved in a crisis might reduce their advertising expenditures, hoping that the public will forget about the crisis, competing firms that are not involved in the crisis may increase their advertising expenditures to take advantage of the situation. For example, Kraft Foods Australia significantly decreased its advertising expenditures on affected brands during its peanut butter product-harm-crisis in 1996. On the other hand, Sanitarium, Kraft's key competitor who was not involved in the crisis, greatly increased its advertising spending (Zhao, Zhao, and Helsen 2011). Therefore, understanding how companies change their advertising strategies in a (pseudo) product-harm crisis is vital not only to the focal firms but also to competing firms in the same industry.

While many studies have examined the impact of advertising and WOM on firms' performance metrics (e.g., Bruce, Foutz, and Kolsarici 2012; Villanueva, Yoo, and Hanssens 2008), scholars have paid less attention to news publicity. In addition, most existing research has typically examined the effect of earned media (i.e., WOM or press coverage) in isolation (e.g., Ahluwalia, Burnkrant, and Unnava 2000; Berger, Sorensen, and Rasmussen 2010). Exceptions to this pattern include Burmester et al. (2015), Cleeren, van Heerde, and Dekimpe (2013), and van Heerde, Gijsbrechts, and Pauwels (2015). Studying the effectiveness of advertising and publicity in game magazines, Burnmester et al. (2015) find that publicity is more effective than advertising in generating video game sales. After studying major product-harm crises in the consumer-packaged goods industry in the United Kingdom and the Netherlands, Cleeren, van Heerde, and Dekimpe (2013) show that negative publicity increases a brand's advertising effectiveness, which is consistent with the hypothesis that any publicity may increase awareness and accessibility, regardless of the valence of the message (Berger, Sorensen, and Rasmussen 2010). van Heerde, Gijsbrechts, and Pauwels (2015) have investigated how media coverage of a price war affects both market share and the competing firms' advertising and price strategy.

Our study combines paid media and earned media to examine how the two types of media affected the two firms' consumer sentiment, as revealed in blog posts (earned media) before and after the crisis. That is, we study how the effects of advertising and news publicity evolved over time on social media during a pseudo-product-harm crisis (Research question 1).

Data and Measurement

Pseudo-Product-Harm Crisis Case

The pseudo-product-harm crisis case that this article examines involved two competing firms (Firm P and Firm T) in the Korean bakery industry. On December 23, 2010, a man, later identified 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 had purchased the bread from a franchise store of Firm P near his home. Immediate responses from the public were similar to those during a typical product-harm crisis; that is, people criticized Firm P for this awful product defect. However, on December 31, 2010, news media revealed that the franchise owner of Firm T had asked his son to purchase the bread from Firm P's store and put the rat inside it, in order to ruin the sales of the nearby competing store. Although the crisis period was only nine days, the sales of both companies during the Christmas season dropped by an estimated 17%–18% from those of the previous year (*Chosun Ilbo* 2011). Since the Christmas season accounts for more than 30% of the annual sales of the Korean bakery industry, the effects of the crisis were especially detrimental.

While Firm P was initially mistaken for the offending firm, it was later proved to be the victim firm; thus, this was a pseudo-product-harm crisis for Firm P. Firm T, whose franchise owner caused the adverse rumors towards Firm P, was the actual offending firm. In this case, Firm T did not immediately admit its responsibility or take appropriate action to resolve the issue.

Data

We gathered the two firms' daily advertising spending data from January 2010 to December 2012 from a large market research company in South Korea. Firm P (the victim firm) and Firm T (the offending firm) are, respectively, the largest and second largest in the Korean bakery industry, with sales in 2012 of $1.6 billion and $0.35 billion, respectively. Advertising spending in this industry shows large variations across months and years. Figure 1 shows the daily TV advertising spending of the two firms during the focal years.

==Figure 1 about here==

To measure daily sentiment about the two brands during the analysis period, we collected consumer-generated blog posts (41,317 for Firm P and 35,029 for Firm T) made between January 2010 and December 2012 on a popular Korean blog site. We also collected online news articles related to the two firms (8,068 for Firm P and 5,011 for Firm T) published during the same period. Then we measured the sentiment of each blog post and news article based on positive and negative keywords (Hu and Liu 2004), as explained in the following subsection.

Measure of Sentiment: Sentiment Analysis

Since our focal firms are based in Korea, the research materials are written in Korean. We leverage OpenHangul project[3] to conduct sentiment analysis on Korean blog posts and news articles (An and Kim 2015). We should note that the method used in OpenHangul is similar to that used in English sentiment analysis; specifically, An and Kim (2015) constructed 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 application programming

[3] http://openhangul.com/

interface that enables us to estimate document-level sentiments in our blog posts and news articles.

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

==Figure 2 about here==

Sentiments in 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 can observe a large increase in negative news volume for both firms during the crisis (December 2010).

Finally, Table 1 summarizes the descriptive statistics of our focal variables. Firm P's average advertising spending ($13,509) is larger than that of firm T ($11,578).

==Table 1 about here==

==Figure 3 about here==

Model-Free Evidence

Table 2(a) shows how the daily average volumes in the blog posts of the three consumer sentiments changed over the three years. The volumes of the three sentiments generally increased over time, except for the volume of neutral sentiment for Firm T; perhaps consumers became more involved in social media and blog posting activities during the period. One-way Analysis of Variance (ANOVA) tests show that the yearly changes were significant for both firms and for all three sentiments. The ratio of positive to negative sentiment also declined for the two firms. For Firm P, the ratio was 10.292 (meaning that there were about 10 positive blog posts per negative post) in 2010, 10.091 in 2011, and 9.063 in 2012. The difference is significant at the 10% level. For Firm T, it was 12.282 in 2010, 9.086 in 2011, and 8.887 in 2012. The difference is significant at the 1% level. Interestingly, the offending firm experienced a sharp decline in the positive-to-negative ratio from 2010 to 2011 while the victim firm experienced only a mild one, suggesting that consumers became more negative towards the offending firm.

Table 2(b) shows how the average daily shares in the blog posts of the three consumer sentiments changed over time. For Firm P, the positive sentiment share increased from 2010 to 2011 but decreased from 2011 to 2012, though a one-way ANOVA test shows that the fluctuation is not statistically significant. For Firm T, the share of positive sentiment constantly increased over the three years, but a one-way ANOVA test again finds that the increase in positive sentiment for Firm T is not statistically significant. Both firms experienced a steady increase in the share of negative sentiment. The average daily share of negative sentiment of Firm P was 8.7% in 2010, 10.1% in 2011, and 10.9% in 2012; for Firm T, it was 7.7% in 2010, 9.8% in 2011, and 12.3% in 2012. One-way ANOVA tests find that the increases are statistically significant at the 1% level for both firms. When it comes to neutral sentiment, on the other hand, both firms saw a consistent decrease over the period. The average daily share for Firm P was

10.4% in 2010, 8.2% in 2011, and 7.5% in 2012; it was 17.0% in 2010, 13.1% in 2011, and 10.5% in 2012 for Firm T. The yearly differences are significant at the 1% level for both firms.

Table 2(c) shows the ratio between the daily shares of Firm T's consumer sentiment and those of Firm P's consumer sentiment (i.e., the daily share of a sentiment about Firm T divided by the daily share of a sentiment about Firm P) over time. These ratios show how the offending firm fared against the victim firm. The ratio of positive sentiments did not significantly change over time; however, the ratio of negative sentiments steadily increased and the ratio of neutral sentiments constantly decreased. These differences are significant at the 5% level. Combined with the results in Table 2(b), these changes in ratio reveal that the share of negative sentiment increased faster for the offending firm than for the victim firm. Overall, these model-free analyses suggest that the deceptive marketing was a self-inflicted wound to the offending firm. In the following section, we develop an econometric model to understand the effect of the pseudo-product-harm crisis in more detail.

==Table 2 about here==

Methodology

We examine how advertising and news publicity influenced consumer sentiment before and after the pseudo-product-harm crisis and how these effects changed in the long run for both firms. To measure consumer sentiment, we use the volume and share of positive, negative, and neutral blog posts. For the pre-crisis analysis, we investigate the one-year period before the crisis (January 1, 2010 – December 22, 2010); for the post-crisis analysis, we examine the two-year period after the crisis (January 1, 2011 – December 31, 2012). To examine how the effects of advertising and news publicity change in the long run, we analyze the years 2011 and 2012 separately. For each firm, the analyses are conducted on the two measures of consumer sentiment (volume and share) for each of the three sentiments. Figure 4 represents our analysis framework.

==Figure 4 about here==

The first set of analyses uses the daily *volumes* of the three consumer sentiments in the blog posts as the dependent variables and regresses them on daily advertising spending, daily news publicity, and control variables such as time trend and weekday/month dummy variables. These analyses serve to indicate whether consumers became more or less responsive to advertising and news coverage after the crisis. For example, an increase in blog volume as a result of advertising post-crisis (but not pre-crisis) suggests that consumers became more responsive to advertising after the crisis, expressing their sentiments on the Internet more actively. The second set of analyses aims to understand how consumer sentiment changed by examining the effects of advertising and news publicity on the *share* of the three consumer sentiments. By analyzing both the volume and share, we can discern whether consumers became more active in spreading their opinions after the crisis, and if so, how this increased activity affected the composition of consumer sentiment. For example, if advertising in the post-crisis period decreases the *share* of positive consumer sentiment and increases that of negative consumer sentiment while increasing the *volume* of the both sentiments, this implies that consumers generate more negative (versus positive) WOM as a result of the advertising.

Let i denote the firms ($i = P$ for Firm P, $i = T$ for Firm T), s denote the three sentiments ($s = Positive, Negative, Neutral$), y denote the years ($y = 2010, 2011, 2012$), and t denote the days ($t =$1/1/2010, 1/2/2010, …). $BLOG\_VOLUME_{i,s,y,t}$ is the daily number of blog posts with sentiment s about firm i on day t of year y. $AD_{i,y,t}$ is the TV advertising spending, and

$NEWSPOS_{i,y,t}$, $NEWSNEG_{i,y,t}$ and $NEWSNEU_{i,y,t}$ are the number of positive, negative and neutral news articles, respectively. Given all of this, Equation (1) examines the effects of advertising spending and news publicity on blog post volumes of the three sentiments.

$$
\begin{aligned}
(1)\quad \log\left(BLOG\_VOLUME_{i,s,y,t}+1\right) &= \beta_{i,s,y,0}+\beta_{i,s,y,AD}\log\left(\textstyle\sum_{k=0}^{K} AD_{i,y,t-k}+1\right)\\
&+\beta_{i,s,y,NEWSPOS}\log\left(\sum_{k=0}^{K} NEWSPOS_{i,y,t-k}+1\right)\\
&+\beta_{i,s,y,NEWSNEG}\log\left(\sum_{k=0}^{K} NEWSNEG_{i,y,t-k}+1\right)\\
&+\beta_{i,s,y,NEWSNEU}\log\left(\sum_{k=0}^{K} NEWSNEU_{i,y,t-k}+1\right)\\
&+ Time\ trend\\
&+ Monthly\ Fixed\ Effects + Weekday\ Fixed\ Effects + \varepsilon_{i,y,s,t}.
\end{aligned}
$$

Because there may be carryover effects of advertising spending and news publicity on blog volume, we include not only the concurrent but also the past values of advertising spending and news volume. For example, $\sum_{k=0}^{K} AD_{i,y,t-k}$ is the sum of the advertising for the current and two previous days if K=2.[4] We control for the time trend effect, as the blog post volume of certain sentiments tends to increase over time (Figure 2). We suspect month and weekday seasonality, in that bakery firms tend to advertise more actively during certain months and weekdays than others. News publicity and WOM activities may also show some seasonal behavior. As such, we control for monthly fixed effects and weekday fixed effects by adding appropriate dummy variables. Equation (1) is estimated by the Ordinary Least Squares method.

Next, let $BLOG\_SHARE_{i,s,y,t}$ be the share of blog posts with sentiment s for firm i on day t of year y, which is defined as follows:

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[4] Varying values of K produces robust results.

$BLOG\_SHARE_{i,s,y,t} = BLOG\_VOLUME_{i,s,y,t}/BLOG\_VOLUME_{i,y,t}$. Equation (2) then examines the effects of advertising spending and news publicity on the share of blog sentiments. Because $BLOG\_SHARE_{i,s,y,t}$ has a value between 0 and 1, we use the logit transformation to estimate the parameters. Equation (2) is estimated by the Maximum Likelihood Estimation method.

$$(2) \quad \text{logit}\left(BLOG\_SHARE_{i,s,y,t}\right) = \gamma_{i,s,y,0} + \gamma_{i,s,y,AD} \log\left(\sum_{k=0}^{K} AD_{i,y,t-k} + 1\right)$$
$$+\gamma_{i,s,y,NEWSPOS} \log\left(\sum_{k=0}^{K} NEWSPOS_{i,y,t-k} + 1\right)$$
$$+\gamma_{i,s,y,NEWSNEG} \log\left(\sum_{k=0}^{K} NEWSNEG_{i,y,t-k} + 1\right)$$
$$+\gamma_{i,s,y,NEWSNEU} \log\left(\sum_{k=0}^{K} NEWSNEU_{i,y,t-k} + 1\right)$$
$$+Monthly\ Fixed\ Effects + Weekday\ Fixed\ Effects + \eta_{i,y,s,t}.$$

Results

Table 3 shows the results of the estimation for Equation (1): the effects of advertising spending and news publicity on the *volume* of the three consumer sentiments before and after the crisis, for the two firms. Before the crisis, advertising had no significant effect on the volume of the three consumer sentiments towards the two firms. That is, before the crisis, advertising was not an important factor in consumers' online WOM activity. However, the effects of advertising on blog post volumes changed dramatically after the crisis. For the victim firm (Firm P), advertising increased the volume of negative as well as positive consumer sentiments in the short run (year 2011). In other words, consumers expressed diverging opinions as the firm's advertising rolled out: one group of consumers showed a favorable response to the firm's advertising, perhaps because they were fans of the bakery brand and believed that the firm was innocent; the other group expressed negative sentiment in response to Firm P's advertising, even after Firm P was cleared of the false charge. A possible reason for this may be a lack of accurate knowledge of the incident: some consumers still may not have been informed of updated news about the crisis. Another reason may be that the pseudo-product-harm crisis generated or exacerbated consumers' distrust of the bakery industry as a whole, subjecting the innocent firm to a negative halo effect (Borah and Tellis 2016). However, in the long run (year 2012), the victim firm became free of the negative effects of advertising, although on the other hand, it did not experience advertising's positive effects. That is, consumers' responses to the victim firm's advertising reverted to the pre-crisis status. In terms of the effects of news publicity, meanwhile, positive news publicity increased the volume of positive consumer sentiment before the crisis; after the crisis (year 2012, specifically), conversely, positive news publicity instead decreased the volume of negative consumer sentiment.

The offending firm (Firm T) also experienced a significant change after the crisis, and this change appears to have been persistent. During the first year after the crisis (year 2011), the offending firm's advertising increased all types of consumer sentiments; simply put, the consumer response to the offending firm's advertising became very active in the first year after the crisis. More important, these significant effects of advertising on consumer sentiment do not disappear even in the long run (year 2012), suggesting a sustained change. One noticeable effect is that the offending firm's advertising increased negative sentiment volume in the long run. In this regard, consumers responded to the offending firm's advertising very differently than to the victim firm's advertising, the impact of which reverted to the pre-crisis status within two years of the crisis. Similar to the results for the victim firm, positive news publicity was for the offending firm associated with positive consumer sentiment both before (year 2010) and after the crisis (year 2011). An important difference is that neutral news increased negative consumer sentiment in the short run (year 2011); that is, consumers responded negatively even to neutral news publicity about the offending firm.

==Table 3 about here==

Table 4 shows the effects of advertising on the *share* of the three consumer sentiments (Equation (2)). The victim firm's advertising did not affect the shares of the three consumer sentiments over the three years. Note, however, that the victim firm's advertising increased the *volume* of both positive and negative consumer sentiments in 2011 (Table 3a). Taken together, these findings indicate that advertising increased the volume of positive and negative consumer sentiments but that the magnitude of the effects was similar for both consumer sentiments. For example, if one unit of advertising spending increased five units of positive consumer sentiment as well as five units of negative consumer sentiment, then the difference in *shares* of the two consumer sentiments would not change, even though their volumes had increased. In terms of the effect of news publicity, meanwhile, negative news publicity decreased neutral consumer sentiment share and neutral news publicity increased neutral consumer sentiment share.

However, a different story unfolds for Firm T, the offending firm. In the short run after the crisis (during the year 2011), advertising decreased the share of positive consumer sentiment and increased the share of negative consumer sentiment. Moreover, the offending firm's advertising increased the volume of both positive and negative consumer sentiments (Table 3(b)). Taken together, these results suggest that consumers spread more negative than positive WOM when they were exposed to the offending firm's advertising during this year. The extent to which the offending firm's advertising generated negative WOM was greater than that to which it generated positive WOM. This result should warn firms against the use of deceptive marketing tactics to increase their performance at the expense of a competing firm.

Interestingly, the offending firm suffered from the same problem in the long run (during the year 2012), although the negative effect of its advertising was dampened to some extent. In 2012, the offending firm's advertising continued to decrease the share of positive consumer sentiment, but it did not increase the share of negative consumer sentiment; instead, advertising increased the share of neutral consumer sentiment during this year. Therefore, negative sentiment about the offending firm persisted as late as two years after the crisis, even though consumers seemed to gradually forget the firm's unethical business practices, as evidenced by the insignificant effect of advertising on negative consumer sentiment share. As to the effects of news publicity, meanwhile, although positive news decreased negative consumer sentiment share, consumers responded negatively even to neutral news about the offending firm. These effects were persistent and did not dissipate even two years after the pseudo-product-harm crisis (year 2012).

==Table 4 about here==

Implications, Limitations, and Future Research

We have studied the consequences of deceptive marketing in the context of a pseudo-product-harm crisis by investigating the effects of paid media (advertising) and earned media (news publicity) on consumer sentiment in social media. Our results suggest that deceptive business practices brought no benefit to the offending firm in either the short or the long run, as the truth was uncovered relatively soon after the crisis. Despite the intentions of the offending firm, the damage to the victim firm was limited. Overall, our research broadens our perspective by examining a special case of product-harm crises that the two firms faced, i.e., a pseudo-product-harm crisis.

Our findings have important implications for firms that need to manage pseudo-product-harm crises, in terms of advertising effectiveness and news publicity. From the perspective of the victim firm, favorable news coverage about the victim firm reduced negative consumer sentiment, but advertising affected consumer sentiment in both positive and negative ways. Therefore, it is probably wise for the victim firm to focus on building appropriate news media strategies to mitigate the negative effects of a pseudo-product-harm crisis, rather than focusing on advertising.

From the perspective of the offending firm, advertising effectiveness greatly declined due to the crisis. Advertising spending surrounding pseudo-product-harm crisis seems to have backfired and exacerbated the crisis. As a result, the offending firm would have been better off if it had not relied on advertising to recover from the pseudo-product-harm crisis. Instead, the offending firm should have taken prompt responsibility before facing the public backlash. As the pseudo-product-harm crisis we examined was initially caused by an inappropriate action on the part of a franchisee, the offending firm believed that a lack of action was the best response to the crisis. However, our analyses show that the offending firm's initial inaction led to massive negative consumer sentiment as well as declining advertising effectiveness, which eventually caused 72 franchisees to go out of business in the first three months after the crisis (*Maeil Business Newspaper* 2011). This indicates that negative consumer sentiment transferred to the entire firm's reputation, even if the deceptive marketing was instigated by a franchise owner rather than the management of the offending firm. Thus, the offending firm needed to carefully monitor and manage the crisis caused by their stakeholders, including franchisees.

In the future, we expect deceptive marketing tactics to bring more harm than good to offending firms, as false claim detection techniques have been developing and will limit the spread of false claims. In response to the proliferation of fake news, major social media players have implemented fact-checking techniques (*Business Insider* 2016; *Google Official Blog* 2016). Thus, false claims generated by deceptive marketing are likely to be quickly identified, limiting the potential benefits of such practices. Thus, such negative tactics that can lead to a pseudo-product-harm crisis do not seem to be an effective strategy in improving firm performance.

A few limitations of our study provide avenues for future research. First, we have examined only one specific case of a pseudo-product-harm crisis from 2010, and caution should thus be exercised when applying our findings to other cases. While it is difficult to collect data across a large number of cases, it would be meaningful to extend our study to other cases with more recent data, in order to test the generalizability of our findings. Second, we have investigated a situation in which the offending and victim firms became known to the public. In many cases where a company is victimized, the true source of adverse rumors may be unknown. Even though our analyses may still be applied to a victim firm, the resulting effects may be different when an offending firm is not known, a topic that future research can examine. Third, while consumer sentiment is an important determinant of firm performance, we could not link the effects of the crisis to the firms' sales or profits due to the unavailability of data. Future studies can extend our work by incorporating those performance metrics in a pseudo-product-harm crisis. Fourth, our study provides insights on how to manage a pseudo-product-harm crisis caused by a firm's stakeholders, such as franchisees. While our analysis reveals the interesting result that the offending firm suffers more than the victim firm from this type of pseudo-product-harm crisis, future studies need to look into whether the negative effects on the offending and victim firms are similar or different when the crisis is caused by the management of the offending firm. Finally, a promising area of research lies in the question of how fake reviews affect consumer decisions. Leaving negative fake reviews of competing products or positive fake reviews of one's own products has become increasingly common as online reviews have become an important driver of sales. Noticing the significance of fake reviews, Amazon filed lawsuits against more than 1,000 people who allegedly offered to hire themselves out as fake reviewers (*USA Today* 2015) and against two sellers who reportedly created fake reviews for their products to influence customers' buying decisions (*TechCrunch* 2016). Fake reviews are also prevalent on many other websites, including Yelp.com and eBay.com. Investigating how fake reviews change consumers' purchase decisions and attitudes towards a company will be a significant avenue for future research.

Compliance with Ethical Standards

- Funding: This study was not funded by any grant.
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References

A.C. Nielsen (2012). Report on global trust in advertising and brand messages. [retelur.files.wordpress.com/2007/10/global-trust-in-advertising-2012.pdf].

Ahluwalia, R. (2002). How prevalent is the negativity effect in consumer environments? *Journal of Consumer Research*, 29 (2), 270-279.

Ahluwalia, R., Burnkrant, R., & Unnava, R. (2000). Consumer response to negative publicity: The moderating role of commitment. *Journal of Marketing Research*, 38 (May), 203–214.

An, J. & Kim, H. (2015). Building a Korean sentiment lexicon using collective intelligence. *Journal of Intelligence and Information Systems*, 21(2), 49-67.

Anderson, C. K., & Lawrence, B. (2014). The influence of online reputation and product heterogeneity on service firm financial performance. *Service Science*, 6 (4), 217–228.

Archak, N., Ghose, A., & Ipeirotis, P. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science*, 57 (8), 1485–1509.

Berger, J., Sorensen, A., & Rasmussen, S. (2010). Positive effects of negative publicity: When negative reviews increase sales. *Marketing Science*, 29 (5), 815–827.

Borah, A. & Tellis, G. (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, N. I., Foutz, N., & Kolsarici, C. (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, B. A., Becker, J., van Heerde, H., & Clement, M. (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. [www.businessinsider.com/bps-new-ad-campaign-just-one-more-dumb-pr-decision-2010-6].

Business Insider (2016). Facebook is going to use Snopes and other fact checkers to combat and bury 'fake news'. [www.businessinsider.com/facebook-will-fact-check-label-fake-news-in-news-feed-2016-12] .

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

Chevalier, J. A. & Mayzlin, D. (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. [news.chosun.com/site/data/html_dir/2010/12/31/2010123101675.html].

Cleeren, K., van Heerde, H., & Dekimpe, M. (2013). Rising from the ashes: How brands and categories can overcome product-harm crises. *Journal of Marketing*, 77 (March), 58-77.

Clemons, E. K., Gao, G., & Hitt, L. (2006). When online reviews meet hyper differentiation: A study of the craft beer industry. *Journal of Management Information Systems*, 23 (2), 149-171.

Cowden, K. & Sellnow, T. (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, R. & Ritchie, R. (2007). The defensive consumer: Advertising deception, defensive processing, and distrust. *Journal of Marketing Research,* 44 (1), 114-127.
Das, S. R. & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science*, 53 (9), 1375–1388.
Dawar, N. & Pillutla, M. (2000). Impact of product-harm crises on brand equity: The moderating role of consumer expectations. *Journal of Marketing Research*, 38 (May), 215–226.
Dellarocas, C., Zhang, X., & Awad, N. (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, R., Edelman, D., & Sarrazin, H. (2012). Demystifying social media. *McKinsey Quarterly*, (April 2012). [www.mckinsey.com/insights/marketing_sales/demystifying_social_media].
Duan, W., Gu, B., & Whinston, A. (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. [www.ft.com/intl/cms/s/0/d4fd0682-b393-11d9-ad2b-00000e2511c8.html#axzz3C0dlau4W].
Godes, D. & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23 (4), 545-560.
Goh, K., Heng, C., & Lin, Z. (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.
Google Official Blog (2016). Labeling fact-check articles in google news. [blog.google/topics/journalism-news/labeling-fact-check-articles-google-news].
Hajli, N. (2016). Ethical environment in the online communities by information credibility: A social media perspective. *Journal of Business Ethics*, 1–12.
Herr, M. P., Kardes, F., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information of persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research*, 174, 454-462.
Hu, M. & Liu, B. (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, H. & Hanssens, D. (2017). Advertising and word-of-mouth effects on pre-launch consumer interest and initial sales of experience products. *Journal of Interactive Marketing*, 37, 57-74.
Kim, S. & Choi, S. (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, Y., Lee, G. M., Pavlou, P. A., & Qiu, L. (2016). The spillover effects of user-generated online product reviews on purchases: Evidence from clickstream data. *Proceedings of 37th International Conference on Information Systems, Association of Information Systems, Dublin, Ireland*, 1-24.
Lu, X., Ba, S., Huang, L., & Feng, Y. (2013). Promotional marketing or word-of-mouth? Evidence from online restaurant reviews. *Information Systems Research,* 24 (3), 596-612.

Luca, M., (2011). Reviews, reputation, and revenue: The case of Yelp.com. *Harvard Business School Working Paper*, September, No. 12-016.
Luo, X., Zhang, J., & Duan, W. (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? [news.mk.co.kr/v3/view.php?year=2011&no=232188].
Meyer, J., Song, R., & Ha, K. (2016). The effect of product placements on the evaluation of movies. *European Journal of Marketing,* 50 (3), 530-549.
Onishi, H. & Manchanda, P. (2012). Marketing activity, blogging and sales. *International Journal of Research in Marketing*, 29 (3), 221-234.
Rishika, R., Kumar, A., Janakiraman, R., & Bezawada, R. (2013). The effect of customers' social media participation on customer visit frequency and profitability: An empirical investigation. *Information Systems Research*, 24 (1), 108-127.
Sentinel Projects (2010). Turn a PR crisis into positive online buzz: Lessons from the Gap. [www.sentinel-projects.com/blog/2010/10/turn-a-pr-crisis-into-positive-online-buzz-lessons-from-the-gap].
Simonson, I. & Rosen, E. (2014). What marketers misunderstand about online reviews. *Harvard Business Review*, January–February.
Stephen, T. A. & Galak, J. (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.
TechCrunch (2016). Amazon sues more sellers for buying fake reviews. [techcrunch.com/2016/10/27/amazon-sues-more-sellers-for-buying-fake-reviews].
The Wall Street Journal (2010). BP tripled its ad budget after oil spill. [www.wsj.com/articles/SB10001424052748703882304575465683723697708].
The Wall Street Journal (2014). Companies turn to social-media coaches. [www.wsj.com/articles/SB10001424052702303949704579461412963008056].
The Wall Street Journal (2015). KFC sues Chinese companies over alleged eight-legged chicken rumors. [www.wsj.com/articles/kfc-sues-chinese-companies-over-alleged-eight-legged-chicken-rumors-1433166317].
The Washington Post (2016). Pizzagate: From rumor, to hashtag, to gunfire in D.C. [http://www.washingtonpost.com/local/pizzagate-from-rumor-to-hashtag-to-gunfire-in-dc/2016/12/06/4c7def50-bbd4-11e6-94ac-3d324840106c_story.html?utm_term=.a930ed018b03]
Tipton, M. M., Bharadwaj, S., & Robertson, D. (2009). Regulatory exposure of deceptive marketing and its impact on firm value. *Journal of Marketing,* 73 (6), 227-243.
Trusov, M., Bucklin, R., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an Internet social networking site. *Journal of Marketing*, 73 (September), 90–102.
Tybout, A. M.,Calder, B., & Sternthal, B. (1981). Using information processing theory to design marketing strategies. *Journal of Marketing Research*, 18 (1), 73-79.
USA Today (2015). Amazon cracks down on fake reviews. [www.usatoday.com/story/tech/2015/10/19/amazon-cracks-down-fake-reviews/74213892].
van Heerde, H. J., Gijsbrechts, E., & Pauwels, K. (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, H. J., Helsen, K., & Dekimpe, M. (2007). The impact of a product-harm crisis on marketing effectiveness. *Marketing Science*, 26 (2), 230–45.

Villanueva, J., Yoo, S., & Hanssens, D. (2008). The impact of marketing-induced versus word-of- mouth customer acquisition on customer equity growth. *Journal of Marketing Research*, 45 (February), 48–59.

Zhao, Y., Zhao, Y., & Helsen, K. (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

(a) Firm P

Variable	Mean	Std. dev.
Advertising spending of firm P on day t ($)	13509.46	29266.15
Volume of positive blog posts about firm P on day t	30.93	26.13
Volume of negative blog posts about firm P on day t	3.57	3.28
Volume of neutral blog posts about firm P on day t	3.19	3.10
Share of positive blog posts about firm P on day t	0.81	0.10
Share of negative blog posts about firm P on day t	0.10	0.09
Share of neutral blog posts about firm P on day t	0.09	0.07
Volume of positive news articles about firm P on day t	6.45	8.05
Volume of negative news articles about firm P on day t	0.59	2.29
Volume of neutral news articles about firm P on day t	0.32	0.92

$\mathrm{N} = 1096$; t = January 1, 2010, …, December 31, 2012

(b) Firm T

Description	Mean	Std. dev.
Advertising spending of firm T on day t ($)	11578.67	34814.86
Volume of positive blog posts about firm T on day t	23.64	17.46
Volume of negative blog posts about firm T on day t	2.98	3.07
Volume of neutral blog posts about firm T on day t	5.34	12.41
Share of positive blog posts about firm T on day t	0.77	0.16
Share of negative blog posts about firm T on day t	0.10	0.10
Share of neutral blog posts about firm T on day t	0.14	0.14
Volume of positive news articles about firm T on day t	3.94	7.24
Volume of negative news articles about firm T on day t	0.43	2.10
Volume of neutral news articles about firm T on day t	0.20	0.89

$\mathrm{N} = 1096$; t = January 1, 2010, …, December 31, 2012

* Firm P is the victim firm and Firm T is the offending firm.

Table 2. Change in Consumer Sentiment over Time

(a) Daily Average Volume

	Firm P				Firm T			
	2010	2011	2012	ANOVA (p-value)	2010	2011	2012	ANOVA (p-value)
Positive (a)	20.874	34.222	37.680	0.000	19.671	24.658	26.574	0.000
Negative (b)	2.263	3.926	4.533	0.000	1.811	3.622	3.503	0.000
Neutral (c)	2.586	3.433	3.555	0.000	7.468	4.726	3.844	0.000
Positive to Negative Ratio (a/c)	10.292	10.091	9.063	0.059	12.282	9.086	8.887	0.000

(b) Daily Average Share

	Firm P				Firm T			
	2010	2011	2012	ANOVA (p-value)	2010	2011	2012	ANOVA (p-value)
Positive	0.809	0.818	0.815	0.482	0.754	0.772	0.772	0.200
Negative	0.087	0.101	0.109	0.000	0.077	0.098	0.123	0.000
Neutral	0.104	0.082	0.075	0.000	0.170	0.131	0.105	0.000

(c) Ratio of Daily Average Share (Firm T to Firm P)

	2010	2011	2012	ANOVA (p-value)
Positive	0.950	0.949	0.952	0.983
Negative	0.909	1.125	1.146	0.020
Neutral	1.916	1.760	1.446	0.022

Table 3. Effects of Advertising Spending and News Publicity on Consumer Sentiment Volume

(a) Firm P

Analysis period →	Before crisis (January 1, 2010 – December 22, 2010)						After Crisis											
							(January 1, 2011 – December 31, 2011)						(January 1, 2012 – December 31, 2012)					
Dep. Var. →	Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment	
Covariate ↓	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	8.761	0.724	-4.888	-0.407	15.583	1.309	-46.621*	-1.710	-56.643**	-2.327	-49.551*	-1.879	41.056	0.846	48.115	1.287	27.223	0.672
AD	0.032	1.295	0.027	1.081	0.010	0.417	0.064**	2.302	0.058**	2.332	0.023	0.869	0.013	0.522	0.001	0.065	0.000	0.020
News Positive	0.124**	2.230	0.007	0.124	0.057	1.044	-0.004	-0.054	-0.031	-0.452	0.054	0.733	-0.095	-1.150	-0.107*	-1.680	-0.061	-0.887
News Negative	-0.002	-0.035	0.059	0.976	0.037	0.622	-0.034	-0.516	0.054	0.914	-0.081	-1.268	-0.085	-1.133	-0.088	-1.526	-0.067	-1.077
News Neutral	0.013	0.188	0.053	0.784	0.020	0.299	-0.082	-0.939	-0.018	-0.226	0.013	0.150	0.037	0.386	0.067	0.906	0.054	0.673
Time trend	-1.089	-0.536	0.940	0.466	-2.484	-1.241	7.541*	1.830	8.746**	2.376	7.665*	1.922	-5.358	-0.774	-6.636	-1.245	-3.671	-0.635
February	0.028	0.123	-0.150	-0.666	0.015	0.065	-0.560**	-2.086	-0.373	-1.555	-0.571**	-2.198	0.232	0.783	0.271	1.185	-0.144	-0.581
March	0.042	0.125	-0.244	-0.728	0.295	0.889	-0.781**	-2.068	-0.793**	-2.351	-0.855**	-2.341	0.333	0.743	0.526	1.521	0.139	0.370
April	0.357	0.777	-0.129	-0.282	0.590	1.306	-1.030**	-2.007	-0.938**	-2.045	-0.953*	-1.919	0.284	0.448	0.616	1.260	0.014	0.027
May	-0.063	-0.104	-0.693	-1.143	0.518	0.863	-1.169*	-1.798	-1.041*	-1.792	-1.381**	-2.195	-0.218	-0.274	0.141	0.230	-0.285	-0.429
June	-0.014	-0.020	-0.648	-0.903	0.679	0.955	-1.346*	-1.720	-1.329*	-1.901	-1.546**	-2.041	0.227	0.250	0.505	0.720	0.003	0.004
July	0.332	0.406	-0.306	-0.376	1.185	1.472	-1.372	-1.493	-1.405*	-1.713	-1.339	-1.507	-0.030	-0.028	0.459	0.556	-0.243	-0.271
August	0.540	0.584	-0.332	-0.362	1.106	1.215	-2.340**	-2.137	-2.524***	-2.581	-2.316**	-2.186	0.349	0.282	0.781	0.821	-0.004	-0.003
September	0.615	0.603	-0.522	-0.516	1.457	1.452	-2.564**	-2.116	-2.732**	-2.525	-2.564**	-2.187	0.728	0.526	1.050	0.984	0.180	0.156
October	0.384	0.344	-0.599	-0.541	1.305	1.190	-3.549**	-2.553	-3.571***	-2.876	-3.168**	-2.356	0.987	0.642	1.236	1.042	0.615	0.479
November	1.059	0.881	-0.307	-0.257	1.628	1.376	-3.505**	-2.334	-3.544***	-2.643	-3.097**	-2.132	0.935	0.555	1.369	1.055	0.301	0.214
December	0.662	0.515	-0.665	-0.520	1.563	1.235	-3.626**	-2.252	-3.515**	-2.444	-3.363**	-2.159	1.176	0.641	1.635	1.156	0.553	0.361
Monday	0.280**	2.206	0.083	0.660	-0.028	-0.226	0.403**	2.704	0.191	1.433	0.227	1.571	0.622***	3.455	0.613***	4.418	0.497***	3.301
Tuesday	0.098	0.743	0.087	0.663	0.066	0.511	0.288*	1.877	0.283**	2.067	0.253*	1.700	0.510***	2.675	0.476***	3.239	0.351**	2.203
Wednesday	0.032	0.232	0.182	1.332	-0.017	-0.122	0.327**	2.089	0.111	0.792	-0.004	-0.025	0.701***	3.479	0.713***	4.597	0.593***	3.524
Thursday	0.217	1.573	0.174	1.271	-0.010	-0.077	0.272*	1.699	0.285**	1.995	0.249	1.606	0.439***	2.194	0.526***	3.415	0.381**	2.286
Friday	0.209	1.556	0.016	0.117	0.116	0.879	0.133	0.850	0.090	0.646	0.116	0.764	0.341*	1.743	0.450***	2.984	0.330**	2.020
Saturday	-0.245*	-1.913	-0.041	-0.321	-0.143	-1.139	0.014	0.094	-0.116	-0.860	0.214	1.464	0.013	0.072	0.071	0.507	0.252*	1.660
R-sq.	0.194		0.111		0.093		0.102		0.129		0.103		0.158		0.193		0.141	

*** Significant at 1%; ** Significant at 5%; * Significant at 10%

(b) Firm T

Analysis period →	Before crisis (January 1, 2010 – December 22, 2010)						After Crisis (January 1, 2011 – December 31, 2011)						After Crisis (January 1, 2012 – December 31, 2012)					
Dep. Var. →	Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment	
Covariate ↓	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	8.288	1.015	-0.931	-0.086	-3.865	-0.247	25.505	1.051	7.821	0.331	61.269***	2.677	61.236	1.209	77.250**	2.151	63.448	1.582
AD	-0.017	-1.183	-0.005	-0.281	-0.033	-1.219	0.052***	3.821	0.050***	3.771	0.048***	3.724	0.038**	2.077	0.028**	2.151	0.041***	2.885
News Positive	0.101***	3.250	0.067	1.631	0.123**	2.076	0.103**	2.008	-0.041	-0.817	0.067	1.393	0.106	1.431	0.036	0.693	0.114**	1.962
News Negative	-0.007	-0.125	0.043	0.610	0.006	0.058	-0.057	-0.921	-0.036	-0.599	-0.097*	-1.658	0.071	0.771	0.030	0.458	0.136*	1.875
News Neutral	0.000	0.000	-0.039	-0.468	-0.108	-0.899	0.088	0.992	0.148*	1.718	0.100	1.193	-0.106	-0.899	-0.082	-0.980	-0.104	-1.120
Time trend	-1.006	-0.732	0.258	0.142	0.736	0.280	-3.447	-0.940	-1.039	-0.291	-9.073***	-2.622	-8.305	-1.149	-10.835**	-2.115	-8.880	-1.553
February	0.223***	2.624	-0.128	-0.646	0.087	0.301	0.151	0.640	0.192	0.835	0.308	1.383	0.195	0.598	0.080	0.346	-0.030	-0.116
March	0.089	1.035	0.029	0.096	0.246	0.571	0.577*	1.728	0.419	1.289	0.616*	1.953	0.313	0.685	0.465	1.439	-0.015	-0.040
April	0.051	0.576	-0.204	-0.499	0.213	0.358	0.672	1.471	0.426	0.957	1.598***	3.707	0.261	0.426	0.477	1.098	0.846*	1.743
May	0.054	0.608	-0.040	-0.078	1.300*	1.737	0.710	1.227	0.457	0.811	1.258**	2.303	-0.722	-0.921	0.159	0.286	-0.244	-0.393
June	0.091	1.031	-0.201	-0.325	-0.222	-0.247	0.844	1.206	0.804	1.180	1.756***	2.659	0.196	0.207	0.831	1.234	0.681	0.905
July	-0.308***	-3.596	-0.126	-0.174	0.236	0.225	1.158	1.414	0.991	1.244	2.370***	3.067	-0.012	-0.011	1.012	1.276	0.698	0.789
August	-0.018	-0.120	-0.099	-0.122	0.043	0.036	-0.028	-0.029	-0.382	-0.413	1.202	1.340	0.180	0.140	1.378	1.513	0.564	0.554
September	0.234	1.038	0.130	0.144	0.597	0.454	-0.046	-0.043	-0.454	-0.442	1.602	1.608	0.142	0.099	1.108	1.084	0.461	0.404
October	0.418	1.347	0.283	0.285	0.331	0.230	0.269	0.232	-0.175	-0.156	2.182**	1.998	0.282	0.176	1.409	1.243	0.813	0.642
November	0.899**	2.299	-0.004	-0.004	0.810	0.528	0.300	0.237	0.066	0.054	2.302*	1.929	0.813	0.462	1.747	1.400	1.419	1.018
December	0.240	0.512	-0.089	-0.080	1.723	1.061	0.296	0.215	0.326	0.242	3.565**	2.735	0.764	0.402	1.699	1.260	1.118	0.743
Monday	0.635	1.160	0.123	1.107	0.161	0.998	0.387***	2.885	0.380***	2.907	0.241*	1.902	0.539***	2.941	0.608***	4.680	0.254*	1.749
Tuesday	0.824	1.335	0.237**	2.093	0.233	1.419	0.374***	2.755	0.312**	2.357	0.147	1.144	0.493**	2.591	0.500***	3.706	0.244	1.623
Wednesday	1.288*	1.873	0.130	1.129	0.100	0.598	0.423***	3.037	0.307**	2.262	0.225*	1.713	0.576***	2.919	0.487***	3.483	0.237	1.517
Thursday	1.338*	1.782	0.088	0.748	0.063	0.372	0.237*	1.701	0.379***	2.792	0.063	0.476	0.477**	2.428	0.456***	3.276	0.144	0.924
Friday	1.672**	2.087	0.131	1.130	0.154	0.915	0.257*	1.848	0.309**	2.288	0.240*	1.834	0.280	1.452	0.402***	2.934	0.056	0.369
Saturday	0.862	1.016	-0.018	-0.159	-0.263	-1.618	-0.142	-1.056	0.062	0.476	-0.232*	-1.827	0.060	0.326	0.170	1.299	0.144	0.990
R-sq.	0.494		0.111		0.355		0.383		0.326		0.423		0.348		0.292		0.324	

*** Significant at 1%; ** Significant at 5%; * Significant at 10%

Table 4. Effects of Advertising Spending and News Publicity on Consumer Sentiment Share

(a) Firm P

Analysis period →	Before crisis (January 1, 2010 – December 22, 2010)						After Crisis (January 1, 2011 – December 31, 2011)						After Crisis (January 1, 2012 – December 31, 2012)					
Dep. Var. →	Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment	
Covariate ↓	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	1.279***	7.764	-2.219***	-10.032	-2.002***	-9.975	1.634***	8.149	-2.335***	-8.298	-2.410***	-10.531	1.304***	7.597	-1.954***	-8.813	-2.403***	-12.289
AD	0.011	0.416	0.011	0.272	-0.026	-0.810	0.020	0.902	0.010	0.290	-0.045	-1.633	0.014	0.818	-0.016	-0.780	0.001	0.022
News Positive	0.036	0.580	-0.022	-0.256	-0.028	-0.357	-0.059	-0.898	0.010	0.105	0.102	1.385	0.063	1.105	-0.081	-1.121	0.023	0.337
News Negative	-0.088	-1.354	0.136	1.507	0.034	0.415	0.039	0.690	0.069	0.932	-0.178**	-2.365	-0.013	-0.242	-0.003	-0.049	0.030	0.426
News Neutral	0.007	0.088	-0.063	-0.613	0.027	0.273	-0.063	-0.894	-0.041	-0.389	0.151*	1.837	-0.055	-0.821	0.062	0.733	0.009	0.095
February	0.181	0.984	-0.188	-0.772	-0.161	-0.653	0.053	0.286	0.049	0.185	-0.222	-1.004	0.187	1.181	0.038	0.182	-0.389**	-1.970
March	-0.039	-0.233	-0.206	-0.899	0.189	0.902	0.153	0.814	-0.104	-0.376	-0.270	-1.212	-0.033	-0.184	0.169	0.728	-0.178	-0.777
April	0.056	0.330	-0.198	-0.861	0.043	0.197	-0.072	-0.406	0.130	0.504	-0.118	-0.553	-0.079	-0.333	0.399	1.371	-0.453	-1.323
May	0.192	0.603	-0.699	-1.488	0.186	0.492	0.030	0.162	0.253	1.000	-0.433*	-1.839	0.101	0.384	0.082	0.248	-0.403	-1.121
June	0.066	0.184	-0.468	-0.902	0.212	0.489	-0.032	-0.186	0.205	0.857	-0.242	-1.155	0.089	0.574	0.036	0.168	-0.177	-0.989
July	-0.300	-0.921	0.127	0.278	0.334	0.822	-0.125	-0.725	0.194	0.766	-0.119	-0.588	0.096	0.620	0.075	0.363	-0.266	-1.430
August	0.003	0.008	-0.109	-0.232	0.015	0.036	0.100	0.428	-0.115	-0.328	-0.096	-0.346	0.133	0.883	0.142	0.721	-0.419**	-2.139
September	-0.033	-0.100	-0.303	-0.653	0.272	0.683	0.104	0.469	-0.065	-0.203	-0.228	-0.809	0.260	1.610	-0.001	-0.006	-0.503**	-2.430
October	-0.121	-0.372	-0.060	-0.131	0.198	0.488	0.029	0.092	-0.173	-0.361	0.039	0.100	0.322**	1.983	-0.309	-1.303	-0.246	-1.372
November	0.147	0.801	-0.135	-0.563	-0.165	-0.662	-0.343	-1.200	0.296	0.689	0.250	0.700	0.340**	2.016	-0.056	-0.255	-0.651***	-2.864
December	0.055	0.141	-0.334	-0.600	0.155	0.322	-0.277	-0.974	0.270	0.591	0.015	0.045	0.187	0.722	0.100	0.311	-0.611*	-1.654
Monday	0.282*	1.927	-0.192	-0.957	-0.324*	-1.666	0.144	1.067	-0.184	-1.005	-0.042	-0.228	-0.115	-0.888	0.021	0.128	0.184	1.077
Tuesday	-0.024	-0.173	0.070	0.384	0.000	-0.001	-0.133	-1.053	0.196	1.187	0.128	0.772	-0.101	-0.733	0.038	0.221	0.081	0.435
Wednesday	-0.076	-0.534	0.167	0.882	-0.042	-0.234	0.225	1.591	-0.102	-0.558	-0.336	-1.629	-0.165	-1.146	0.095	0.521	0.135	0.706
Thursday	0.126	0.840	0.017	0.088	-0.236	-1.163	-0.052	-0.391	0.059	0.324	0.053	0.308	-0.252*	-1.808	0.197	1.150	0.168	0.906
Friday	0.156	1.055	-0.317	-1.450	-0.037	-0.204	-0.068	-0.519	-0.032	-0.177	0.185	1.120	-0.150	-1.060	0.073	0.414	0.104	0.533
Saturday	-0.090	-0.696	0.141	0.817	0.034	0.197	-0.068	-0.540	-0.228	-1.189	0.325**	2.047	-0.187	-1.447	-0.071	-0.415	0.395**	2.312
Log likelihood	308.20		442.04		390.84		351.01		418.98		505.25		354.79		423.69		543.53	

*** Significant at 1%; ** Significant at 5%; * Significant at 10%

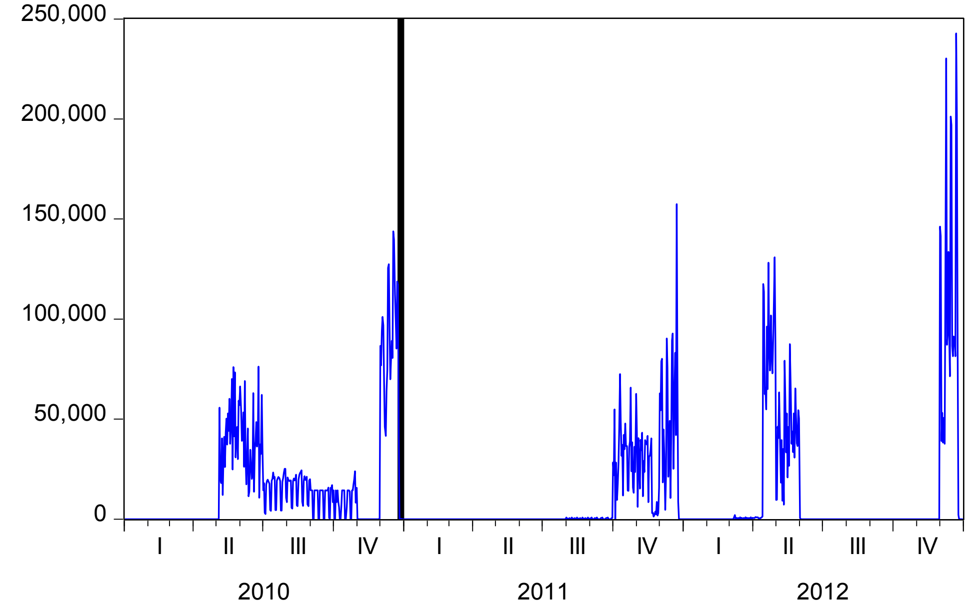
(b) Firm T

Analysis period →	Before crisis (January 1, 2010 – December 22, 2010)						After Crisis (January 1, 2011 – December 31, 2011)						After Crisis (January 1, 2012 – December 31, 2012)					
Dep. Var. →	Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment		Positive Sentiment		Negative Sentiment		Neutral Sentiment	
Covariate ↓	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Intercept	1.396***	7.598	-2.185***	-11.958	-2.342***	-7.387	1.154***	6.625	-2.223***	-10.366	-1.788***	-8.191	1.443***	5.792	-2.365***	-6.854	-2.253***	-7.411
AD	-0.021	-0.840	-0.006	-0.136	0.029	0.967	-0.039***	-2.840	0.069***	3.027	0.012	0.885	-0.032*	-1.680	-0.014	-0.552	0.063***	2.870
News Positive	-0.075	-1.397	-0.032	-0.465	0.177***	2.625	0.072	1.433	-0.137**	-2.349	-0.005	-0.084	-0.046	-0.644	-0.068	-0.786	0.136	1.525
News Negative	-0.095	-1.070	0.009	0.080	0.113	1.022	0.007	0.117	0.062	0.842	-0.073	-0.883	-0.040	-0.422	-0.058	-0.478	0.201*	1.788
News Neutral	0.134	1.184	0.034	0.255	-0.243	-1.605	-0.072	-0.831	0.034	0.320	0.126	1.271	-0.021	-0.169	0.300*	1.900	-0.226	-1.452
February	0.031	0.141	-0.277	-1.279	0.184	0.490	-0.146	-0.781	0.318	1.410	0.002	0.007	0.412	1.316	-0.017	-0.038	-0.509	-1.379
March	-0.180	-0.888	-0.043	-0.237	0.387	1.113	0.114	0.574	0.248	1.068	-0.414	-1.469	0.372	1.201	0.307	0.738	-0.844**	-2.040
April	-0.012	-0.056	-0.478**	-2.083	0.364	1.043	-0.375**	-2.063	0.209	0.887	0.407*	1.826	-0.268	-0.975	-0.054	-0.118	0.468	1.548
May	-0.801***	-4.350	-0.671***	-2.619	1.449***	4.778	-0.047	-0.240	0.353	1.536	-0.214	-0.812	0.025	0.087	0.602	1.581	-0.521	-1.441
June	0.043	0.196	-0.144	-0.743	0.100	0.262	-0.259	-1.428	0.623**	2.956	-0.153	-0.609	-0.242	-0.998	0.472	1.463	0.100	0.333
July	-0.181	-0.880	-0.328	-1.576	0.582*	1.717	-0.287	-1.528	0.563**	2.489	-0.020	-0.083	-0.440*	-1.885	0.652**	2.088	0.253	0.880
August	0.135	0.599	-0.473**	-2.121	0.218	0.580	0.675***	2.717	-0.857**	-2.329	-0.504*	-1.717	-0.257	-1.057	0.975***	3.266	-0.893	-1.617
September	-0.058	-0.271	-0.625**	-2.479	0.550	1.608	0.677***	2.816	-0.794**	-2.363	-0.469	-1.632	0.569*	1.672	0.115	0.257	-1.043**	-2.328
October	0.017	0.080	-0.217	-1.090	0.200	0.551	0.356	1.586	-0.468	-1.393	-0.259	-0.944	0.204	0.700	0.228	0.597	-0.455	-1.159
November	0.009	0.033	-0.679*	-1.806	0.427	1.128	0.094	0.455	0.258	1.058	-0.408	-1.391	-0.061	-0.221	0.292	0.780	-0.002	-0.006
December	-1.176***	-3.290	-0.614	-0.998	1.694	3.623	-0.860***	-4.200	-0.003	-0.010	1.087***	4.773	0.707*	1.901	-0.368	-0.620	-0.930**	-2.208
Monday	0.252	1.599	-0.178	-0.828	-0.370*	-1.799	0.075	0.577	0.045	0.301	-0.213	-1.299	-0.065	-0.352	0.560**	2.334	-0.533**	-2.419
Tuesday	-0.045	-0.305	0.265	1.458	-0.118	-0.623	0.241*	1.721	-0.097	-0.597	-0.375**	-2.098	0.012	0.061	0.255	0.951	-0.396*	-1.806
Wednesday	0.082	0.545	0.061	0.303	-0.167	-0.893	0.035	0.261	-0.018	-0.108	-0.035	-0.219	0.147	0.715	0.164	0.587	-0.666***	-2.614
Thursday	0.158	1.006	0.119	0.599	-0.295	-1.493	0.022	0.166	0.155	0.992	-0.174	-1.062	0.179	0.861	-0.143	-0.462	-0.427*	-1.868
Friday	0.027	0.175	0.110	0.557	-0.125	-0.665	-0.098	-0.750	0.046	0.282	0.064	0.419	0.016	0.081	0.458*	1.811	-0.561**	-2.406
Saturday	0.133	0.882	0.181	0.976	-0.286	-1.470	0.110	0.838	0.025	0.164	-0.182	-1.160	-0.078	-0.423	0.089	0.325	0.004	0.022
Log likelihood	219.06		474.34		228.21		277.39		453.23		353.60		149.12		236.23		308.32	

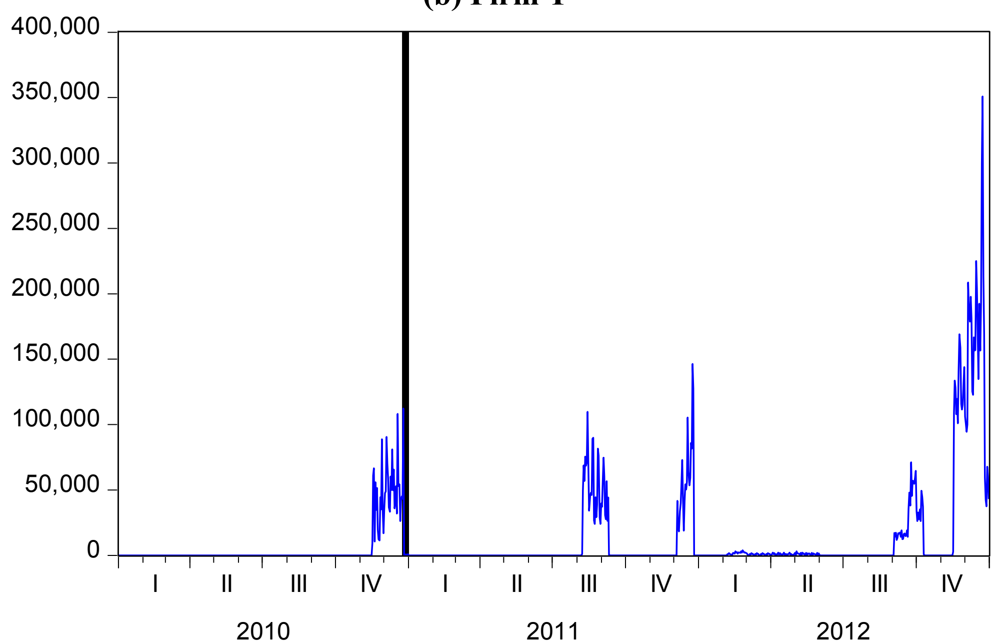
*** Significant at 1%; ** Significant at 5%; * Significant at 10%

Figure 1. Daily Advertising Spending (Unit: $)

(a) Firm P



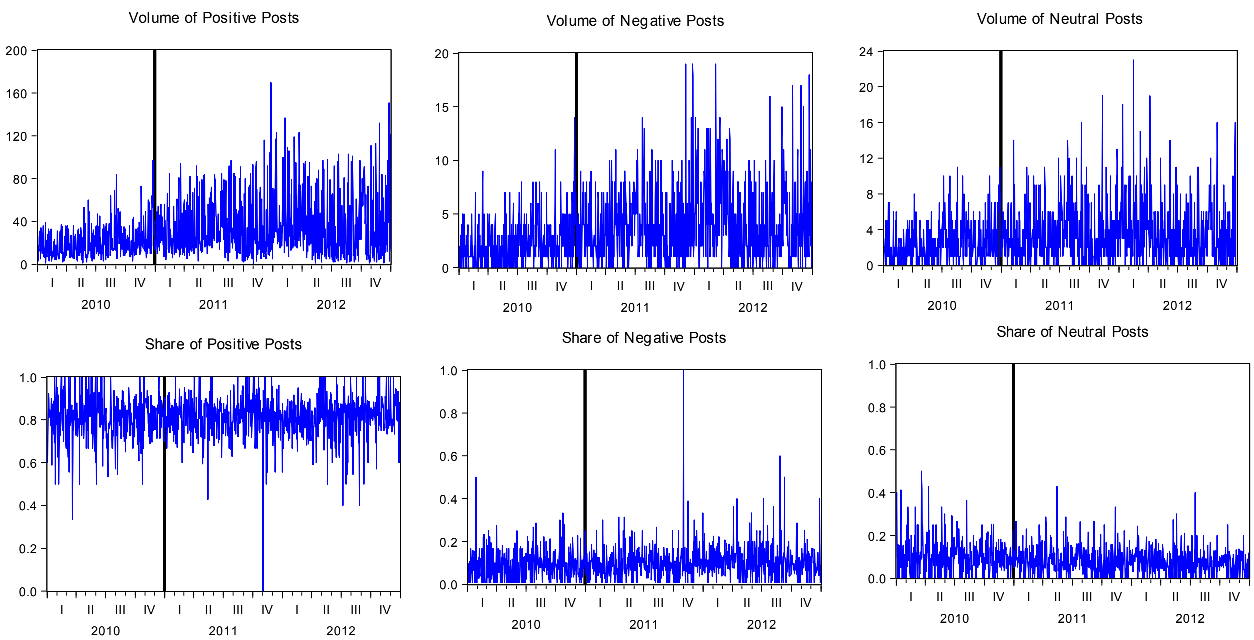
(b) Firm T



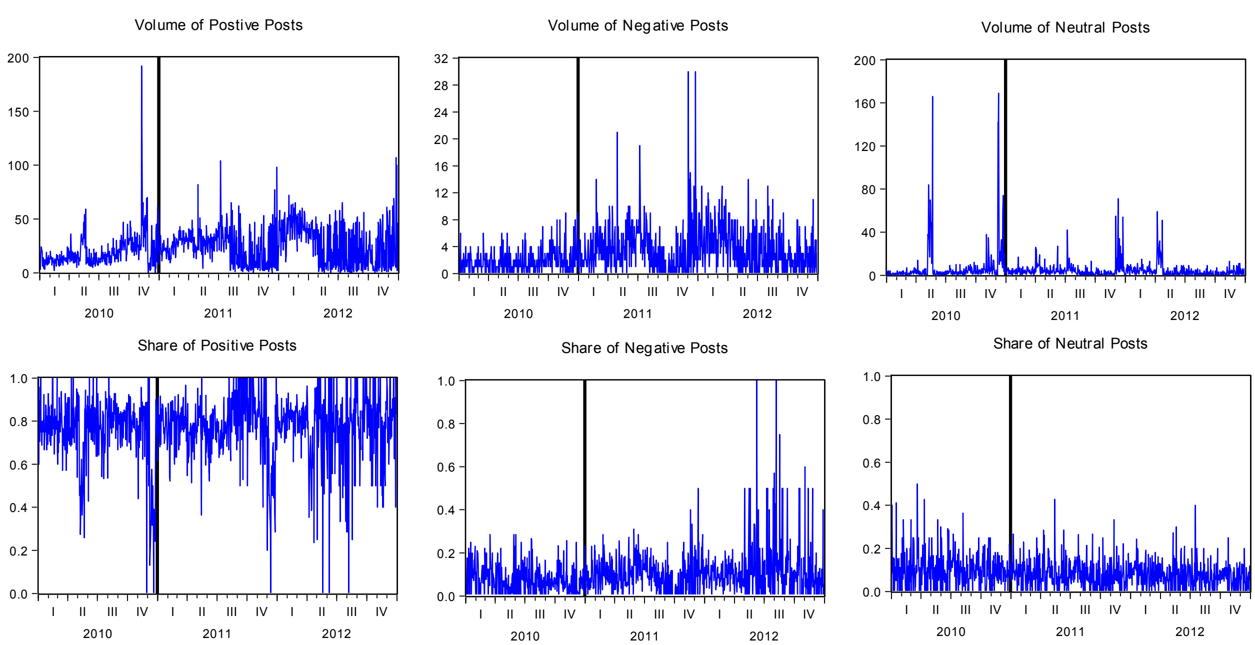
The vertical lines represent the start and end dates of the crisis (9 days).

Figure 2. Daily Volume and Share of Positive, Negative, and Neutral Blog Posts

(a) Firm P



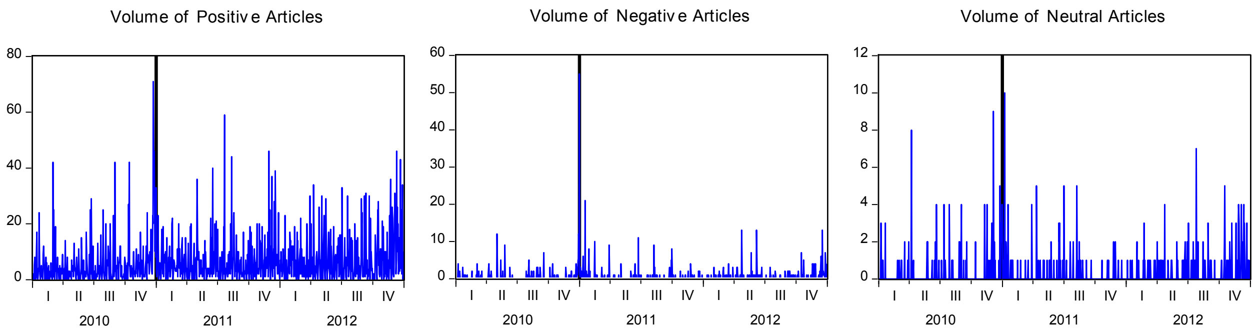
(b) Firm T



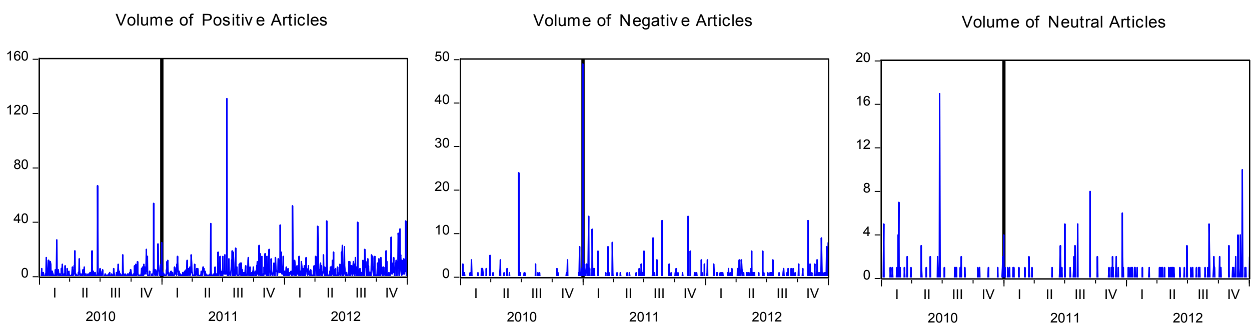
The shaded areas represent the crisis period.

Figure 3. Daily Volume of Positive, Negative, and Neutral News Articles

(a) Firm P

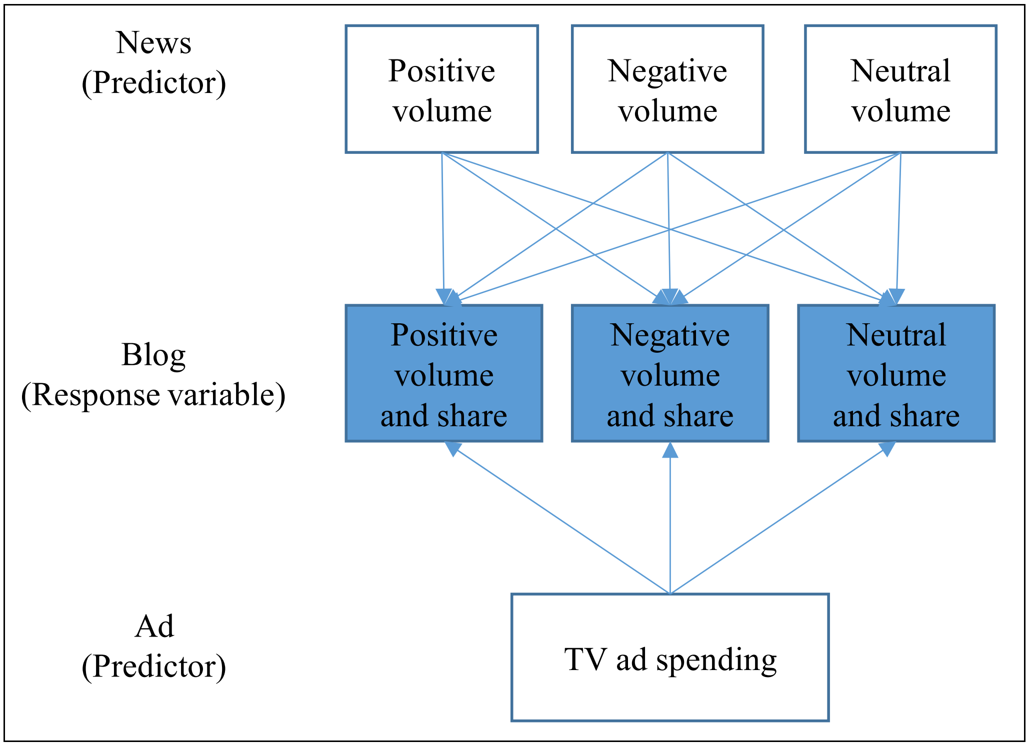


(b) Firm T



The shaded areas represent the crisis period.

Figure 4. Analysis Framework



Analysis periods: 2010 (before the crisis) and 2011-2012 (after the crisis)