DO PEPSI DRINKERS TALK ABOUT SLEEPWALKER?
THE EFFECTS OF SELF-PRESENTATION AND CONFORMITY IN COMPETING WORD-OF-MOUTH

Research-in-Progress

Qing Chen
Department of Information Systems
National University of Singapore
13 Computing Drive, Singapore 117417
chenqing@comp.nus.edu.sg

Tuan Quang Phan
Department of Information Systems
National University of Singapore
13 Computing Drive, Singapore 117417
phantq@comp.nus.edu.sg

Khim Yong Goh
Department of Information Systems
National University of Singapore
13 Computing Drive, Singapore 117417
gohky@comp.nus.edu.sg

Abstract

While advertisers increase spending on marketing campaigns, little is known about its effectiveness for the firm and for its competitors. In this study, we explore consumer responses to TV advertising of the 2010 Superbowl show. We investigate how peer exposure to brands affects word-of-mouth generation for the brand and its competitors using a unique dataset with 1.3 million users’ activities during 72 days in a social network site. We find that users with more friends on SNS have a higher tendency to generate WOM about TV commercials. Second, peer exposure of a brand has a negative relationship with users’ tendency to generate WOM about both the same brand and competing brands. Particularly, one additional friend’s mention would decrease WOM probability of the brand by 0.3% and that of its competitor by 0.1%. Our work provides novel insights on the diffusion of WOM and practical implications for social media marketing.

Keywords: Word of mouth, Social networks, E-business, Competition
Introduction

With the explosive popularity of social network sites (SNS) recently, marketers have become keen on the intense online communication at the individual-level for marketing purposes like brand or product promotion. On one hand, word-of-mouth (WOM) has been documented to have significant impact for brand awareness (Reingen et al. 1984), product evaluation (Godes and Silva 2012; Moe and Schweidel 2011) and sales (Chevalier and Mayzlin 2006; Ghose and Ipeirotis 2010; Godes and Mayzlin 2004). On the other hand, interpersonal connections in social networks have also been perceived as an effective mechanism for peer influence (Brown and Reingen 1987; Ellison and Fudenberg 1995) and content diffusion (Johan 1967; Susarla and Tan 2012). Although numerous studies have examined the value of WOM on SNS, there are still several research gaps that motivate our work.

First, the majority of prior studies focused on within-product WOM effects (Chevalier and Mayzlin 2006; Ghose and Ipeirotis 2010; Godes and Mayzlin 2004), which studies the impact from a product-related WOM on its own sales or consumer evaluations. However, in the real world, consumers are often influenced by information from multiple products or even competing products. Hence, how consumers respond to WOM from competing products or brands remains an unanswered question that we focus on in this study. Second, while several recent studies have demonstrated that network position in a social network has a substantial impact on content diffusion (Stephen and Toubia 2010; Susarla and Tan 2012; Yoganarasimhan 2011), only a few studies (Katona et al. 2011) have dealt in an in-depth manner into how interpersonal interactions affect WOM diffusion. We address this issue using detailed individual-level data on user behavior from a large social network site. Third, although extant research has identified several factors that may influence individuals’ decision to generate WOM (Dellarocas and Narayan. 2006; Moe and Schweidel 2011), few studies have studied consumers’ incentive to generate WOM from a status reward perspective (Fehr and Falk 2002). This is challenging due to the identification problem (Manski 1993; Shalizi and Thomas 2011). Nevertheless, we address this issue with an offline event which provides an exogenous impact on SNS. Finally, apart from extant literature that mainly analyzes marketing outcomes in a single channel (Godes and Mayzlin 2009; Katona et al. 2011), this study attempts to shed light on consumer responses to cross-channel marketing campaigns. Specifically, this paper exploits users’ WOM generation on SNS after exposure to prominent TV commercials on TV broadcast media.

In sum, the objective of this paper is to explore the impact of peer exposure from competing WOM on content diffusion on SNS at the individual consumer level after an exogenous event - the exposure to TV commercials.

In particular, we focus on the event of the 2010 Superbowl Show XLIV by using TV commercials from the event as an exogenous event on SNS. Reported by a digital marketing agency (i.e., Ymarketing), Super Bowl XLIV became the most-watched U.S. television program in history, drawing an average audience of 111 million viewers. Distinguished from other ordinary TV advertisements, commercials on the Superbowl Show debut with highly creative or artistic conceptualizations, appealing to millions of audiences. These prominent offline commercials provide opportunities for us to examine how content about brands diffuses on SNS after the Superbowl Show. More interestingly, we focus on two competing brands, Coca Cola and Pepsi. The former brand purchased the TV advertising slots to showcase two new but different commercials titled the Sleepwalker and Hard Times; while the latter brand, Pepsi, did not. Despite the difference in marketing strategy, both Coca Cola and Pepsi witnessed an increase in WOM on SNS according to our statistics. Specifically, we collect data about users’ activities on a large SNS during a 72-day period: 38 days before the Superbowl Show (as controls for users’ pre-existing interest for brands) and 34 days after (the focal period). The brand’s content diffusion is tracked by checking whether a user generates WOM about the brand (Coca Cola or Pepsi) after the Superbowl show. The focal interest of our study is how a user is affected by peer exposure to generate WOM about a brand after his or her friends discussed the same brand or a competing brand.

Based on our analysis, we find three preliminary results. First, users with more friends on SNS have a higher intrinsic tendency to generate WOM about brands showcased on TV commercials. Second, peer exposure in WOM about both the same brand and a competing brand has a negative impact on a brand’s content diffusion on SNS. Third, with time passing by from the Superbowl show, users are less likely to be impacted by peer exposure to generate WOM about commercial brands. Our findings provide the following implications. Theoretically, our study enlightens new perspectives for the theory of diffusion.
While prior work suggests a positive network effect or a spillover effect for product diffusion or information cascades (Bikhchandani et al. 1992; Salner and Shepard 1995), our findings show strong peer exposure of a brand’s discussion may also impede the diffusion. Practically, our findings suggest that marketers should be cautious in implementing marketing strategies from the consideration of consumers’ intrinsic motivations.

**Theoretical Development**

**Related Literature**

Word-of-Mouth (WOM), which refers to customers’ conversations for brand or product-related information diffusion, has attracted extensive research interests since Katz et al. (1955) and Rogers (1995). Traditionally, WOM has been documented to have a significant influence on consumers’ decision process or product preference by a stream of past studies (Arndt 1967; Brown and Reingen 1987; Ellison and Fudenberg 1995). In recent years, with the emergence of various forms of online communities, researchers have the opportunity to directly measure WOM and to quantitatively estimate the economic impact of large-scale communications online. For instance, Chevalier and Mayzlin (2006) validated a significant relationship between consumer’s reviews and book sales in two websites. Godes and Mayzlin (2004) examined the dispersion of conversations across online communities and found it has considerable influences on the popularity of television shows. Furthermore, Chevalier and Mayzlin (2006) and Duan et al. (2008) demonstrated that volume and valence are two critical indexes for online reviews that have strong explanation power for sales. Ghose and Ipeirotis (2010), however, suggest that volume and valence measures of WOM cannot fully reflect the whole information embedded in consumer reviews and their empirical findings revealed that the textual characteristics of a review also have significant effect on sales.

In addition, to measure the economic impact of WOM, numerous studies also provide evidences about different factors that drive WOM. Anderson (1998) used customer satisfaction data to propose a utility-based model and found that very dissatisfied customers and very satisfied customers are most likely to engage in WOM. Similarly, Bowman and Narayandas (2001) measured WOM through surveys and found that loyal customers engage only in negative WOM and only when they are dissatisfied. Furthermore, two recent studies looked at the WOM incidence and evolution from a dynamic view. Specifically, Moe and Schweidel (2011) identified selection effects and adjustment effects respectively in explaining consumers’ incidence decision and evaluation about WOM while Godes and Silva (2012) investigated two distinct dynamic process: time and sequence of previous WOM.

Another related stream of research is content diffusion through social network analysis. For instance, Reingen et al. (1984) reveal that interpersonal relationships have a substantial impact on brand choice. Moreover, Brown and Reingen (1987) explored the different roles different roles played by weak and strong social ties in macro-level and micro-level WOM phenomena. Recently, in the online context, a few studies also examined the impact from network indices (e.g. centrality, betweenness, and network closure) on content diffusion. For example, Katona et al. (2011) analyzed the diffusion of a technology service and revealed that interpersonal network structures, which reflect the aggregated social influence, have a significant effect on consumers’ adoption decisions. Likewise, Susarla and Tan (2012) and Yoganarasimhan (2011) studied the diffusion of YouTube videos and provided consistent evidences that network connections are one major channel for videos to disseminate and eventually network positions such as centrality and betweenness have strong relationships with the viewship of videos. Generally, this stream of work explored the diffusion process though social connections from the perspective view of network analysis.

**Hypotheses Development**

In this study, by focusing on user activities in an online SNS, we analyze consumers’ responses to peer exposure in generating WOM about prominent commercials after a highly popular TV show. Primarily, it is essential to understand the underlying incentives that motivate a user to generate WOM on SNS. In the literature, a few intrinsic motivations have been examined for why users respond to peer influences. For instance, consumers can receive higher utility through adopting a new technology product (Katona et al. 2011) or gain emotional happiness through watching a fascinating video (Susarla and Tan 2012;
Yoganarasimhan 2011). In our research context, although conversations about certain brands seem not to bring about direct economic or emotional benefits, perspectives from the self-presentation theory and social conformity theory provide a theoretical grounding to understand such consumer response on social networks.

According to the literature, Leary (1995) defined self-presentation as the process people attempt to manage the impressions that he or she makes on other people. More specifically, it is “the process by which people convey to others that they are of a certain kind of person or possess certain characteristics”. Extending from the self-presentation theory, Kim et al. (2012) suggests that people can receive intrinsic reward by influencing others and several researchers have adopted this statement to explain individual behavior in electronic knowledge contribution (Kankanhalli et al. 2005; Wasko and Faraj 2005) and online communities purchase(Kim et al. 2012). In our research settings, Superbowl commercials are highly talked about events during the live broadcast television show. Therefore, people might have an intrinsic interest to bring this appealing offline event to the online platform by generating WOM about those prominently showcased commercials’ brands on SNS. Thus, we hypothesize that users on SNS have motivations to generate WOM about prominent commercials’ brands amongst their social groups to gain self-presentation rewards. In addition, the more friends a user has on SNS, more people are potentially influenced by WOM about the brands showcased in commercials, which in turn motivate a higher level of self-presentation rewards to the user. Hence, we propose our first hypothesis:

**H1:** The number of friends on SNS has a positive impact on a user’s tendency to generate WOM about brands after an exogenous offline event.

Nevertheless, the intrinsic reward a user can earn by WOM also depends on the number of people that have already been informed of the commercials. It is less “cool” or “influential” to repeat a topic on SNS when many people around have already been aware of it. Specifically, if WOM about Superbowl commercials has been highly discussed by friends within a user’s social group, more friends in the social network might have noticed the Superbowl commercials. Therefore, there would be less marginal influence a user can earn by generating WOM about the same commercials. For this reason, it is reasonable to argue that users are less likely to generate WOM about a brand when there is strong peer exposure about the same brand in the social group.

**H2:** Peer exposure to a brand’s commercial on a user’s social network has a negative impact on the user’s tendency to generate WOM about the same brand.

Apart from peer exposure from the same brand, effect from competing brand’s WOM is another crucial driver for user behavior that cannot be overlooked. We look towards social conformity theory to address issues of conflicting messages and opinions. According to social conformity theory (Crutchfield 1955), conformity is a type of social influence involving a change in belief or behavior in order to fit in with a group. In other words, conformity motivation suggests that most people like to receive social approval and to try to avoid social disapproval. The intuitive argument for this statement is that approval generally would make people proud and happy whereas disapproval from others would cause embarrassment and shame. Following this logic, in a user’s social network, heated discussions about a brand’s WOM represents the overall preference or interest towards this brand within the social group. As a result of conformity pressures, the user might have a lower tendency to generate WOM about a competing brand. Therefore, the third hypothesis is put forward as follows:

**H3:** Peer exposure to a brand’s commercial on a user’s social network has a negative impact on the user’s tendency to generate WOM about the competing brand.

Moreover, the impact from Superbowl TV commercials would decay over time. As time passes by from the Superbowl event, past commercials are no longer “hot” topics and people care less about them. This means the intrinsic rewards generated by WOM about those brands on SNS also decreases from both the social conformity and self-presentation perspectives. Therefore, the later a user is impacted by peer exposure about the Superbowl show, the less likely he or she would follow the norm by generating WOM about the brand.

---

1 Competing brands in this study refers to different brands of same product category that compete for sales in the same market segment.
**H4:** The later the peer exposure to an exogenous offline event, the lower tendency a user has to generate WOM about the exogenous event.

**Empirical Model Specification**

With respect to hypotheses, we construct the dependent variable of our interest as a binary choice on whether or not a user on SNS generates WOM about certain brands after the Superbowl show. For user \( i \), we define \( \text{GenC}_i = 1 \) if user \( i \) generated WOM about a brand \( C \) during our observed period after Superbowl show and \( \text{GenC}_i = 0 \) otherwise. Similarly, the other dependent variable \( \text{GenP}_i \) is constructed to represent WOM generation about a competing brand \( P \).

In our model, user \( i \)'s probability (to measure tendency) to generate WOM about certain brands is a function of impact of peer exposure and individual-specific factors. To measure the level of peer exposure of a brand in user \( i \)'s social network, we count the number of user \( i \)'s friends that have generated WOM about this brand before. Therefore, our main independent variables include the total number of friends a user has on SNS (\( \text{Friendscount}_i \)), number of friends who generate WOM about brand \( C \) before the user but after the Superbowl show (\( \text{NFriendsC}_i \)), number of friends who generate WOM about brand \( P \) before the user but after the Superbowl show (\( \text{NFriendsP}_i \)). In addition, to measure the time lag of peer exposure from the Superbowl show, we construct two time gap variables: \( \text{TimeGapC}_i \) and \( \text{TimeGapP}_i \) for different brands respectively. Specifically, the time gap variables count the days from the Superbowl show to the median day a user \( i \)'s friends generated WOM about brand \( C \) and brand \( P \).

Apart from the factors identified in the four hypotheses, other variables may also affect a user’s behavior in generating WOM about a brand on SNS. Intuitively, whether a user is active on SNS may have a substantial impact. For example, a user who posts information or sends messages frequently is expected to have a higher probability to generate WOM about brands after the Superbowl show. Hence, we use the following control variables to measure extent of content generation or sharing by user \( i \): the number of days since user \( i \) registered on the SNS (\( \text{SNage}_i \)), the total number of recorded actions user \( i \) has on the SNS during our observed period (\( \text{Activity}_i \)). We also include a gender dummy of user \( i \) (\( \text{Female}_i \)). Moreover, users with intrinsic interests or preferences for a certain brand are more likely to generate WOM about the brand after the Superbowl show. To control for such intrinsic propensity, two binary variables (\( \text{PtimeP}_i, \text{PtimeC}_i \)) are constructed to indicate whether user \( i \) has generated WOM about the two brands during the last month before Superbowl show, respectively.

We use a logit model in our empirical analysis. Take the brand \( P \) as example, that is:

\[
\Pr(\text{GenP}_i = 1 \mid X_i) = \Lambda(\beta_0 + X_i \beta) = \frac{e^{\beta_0 + X_i \beta}}{1 + e^{\beta_0 + X_i \beta}}
\]

\[X_i \beta = \beta_1 \text{Friendscount}_i + \beta_2 \text{NFriendsC}_i + \beta_3 \text{NFriendsP}_i \]

\[+ \beta_4 \text{TimeGapC}_i + \beta_5 \text{TimeGapP}_i + \beta \text{Controls} \]

\[y^* = \beta_0 + X \beta + u \]

Particularly, for the error term \( u \) in the underlying latent utility (3), it represents individual-level unobservables that are might be correlated with user \( i \)'s probability to talk about brands. For instance, it contains offline communications that are not captured in our data, or stochastic shocks that compels a user to generate WOM. Additionally, we also acknowledge there might be missing information about a user’s communication about brands or measurement errors in user \( i \)'s intrinsic preferences for brands and these errors are also included in \( u \).

**Data**

In this paper, we study the time periods surrounding the Superbowl XLIV Commercial which aired on broadcast television on the evening of February 7th, 2010. In the U.S, the Superbowl sporting event is a highly watched TV program that attracts 100 million audiences on average, offering a highly sought-after opportunity for businesses to advertise their brands. Specifically, we focus on two competing brands -
Coca Cola and Pepsi. In 2010, Coca Cola purchased two 60-seconds slots for commercials during Superbowl show, each valued at about USD 5 million. On the other hand, the rival brand - Pepsi did not purchase any commercials slots during the show. Unexpectedly, both Coca Cola and Pepsi experienced increased WOM shortly after the Superbowl commercial show. Specifically, we observe that Coca Cola’s WOM increased by about 6% while Pepsi’s WOM increased by nearly 30%. Therefore, it is worthwhile to investigate the within-brand and cross-brand effects on SNS at the individual level.

We obtained our data through collaboration with one of the largest SNS in the World. This SNS was started in 2004 and grew to over 900 million users worldwide currently. The raw dataset consists of three parts: user action content from January 1st 2010 to March 13th 2010, user profile information of over 1.4 million undergraduate students who were in the graduating class of 2008 through 2011 from 134 US universities. Additionally, we included the complete users’ friendship relationship data. The whole 72-day period is divided into two periods: the first period from January 1st 2010 to February 6th 2010 is treated as the control period to account for users’ existing prevailing interest for Coca Cola and Pepsi (discussed in the last section); the second period from February 7th 2010 to March 13th 2010 is the focal period during which we observe how users respond to TV commercials by generating WOM about Coca Cola and Pepsi during the second 34-day period.

In the construction of our data, we first randomly select 29,458 users (sampling ratio of 2%) from the whole 1.4 million populations of users. After merging with the friendship data and excluding user records with duplicate or missing data in the user profile data set, we obtain our final sample of 17,942 users. Then, we use regular expressions to search for keywords related to the two brands, including “Coca Cola”, “Coke”, “Pepsi” and “PepsiCo” through sampled users’ content activities in the second period, to identify those users that generated WOM about the two brands after the Superbowl show. We found 257 users who generated WOM about Coca Cola and only 42 users who generated WOM about Pepsi in our sample. Moreover, for each user in our sample, we search through his or her activities in the controlled period to measure whether he/she generated WOM about Coca Cola and Pepsi before the Superbowl show. Besides, we also counted all the SNS actions of sample users during our observed period to measure a user’s level of activity on the SNS.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>0.519</td>
<td>0.499</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>GenP</td>
<td>0.003</td>
<td>0.048</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>GenC</td>
<td>0.014</td>
<td>0.119</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>SNage</td>
<td>1,791.01</td>
<td>456.08</td>
<td>708</td>
<td>2,657</td>
</tr>
<tr>
<td>Activity</td>
<td>538.77</td>
<td>915.89</td>
<td>0</td>
<td>22,977</td>
</tr>
<tr>
<td>Friendscount</td>
<td>130.38</td>
<td>117.05</td>
<td>1</td>
<td>1,123</td>
</tr>
<tr>
<td>PtimeP</td>
<td>0.002</td>
<td>0.046</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>PtimeC</td>
<td>0.013</td>
<td>0.114</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Location_Site</td>
<td>0.013</td>
<td>0.113</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Location_Team</td>
<td>0.0015</td>
<td>0.038</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table1 and 2 report the cross-sectional data description. The sample contains 17,942 users in total. Our selected sample has students across 132 universities out of 134 universities in the complete dataset. The mean value of Female is 0.519, meaning our sample has about equal distributions across the two genders. In our sample, nearly 0.3% users generate about Pepsi after the Superbowl show while the percentage for Coca Cola is around 1.4%. Furthermore, we observe from PtimeP and PtimeC that only a small portion of users had WOM about both Pepsi and Coca Cola before Superbowl commercial. In addition, to capture the geographically different level of interest for Superbowl XLIV, we included the Location_Site dummy to represent users who were studying or living in Miami (the city hosted Superbowl XLIV in 2010) and the
dummy Location_Team for users studying or living in New Orleans or Indianapolis (the two cities with teams competing in the Superbowl finals game that year). In Table 2, since peer exposure is measured before the time a user generates WOM about a focal brand, the values of NFriendP, NFriendC, TimeGapP and TimeGapC are different when analyzing brands' WOM generation for Coca Cola and Pepsi.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coca Cola</th>
<th>Pepsi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Std.Dev</td>
<td>Mean</td>
</tr>
<tr>
<td>NFriendsP</td>
<td>0.345</td>
<td>0.696</td>
</tr>
<tr>
<td>NFriendsC</td>
<td>2.06</td>
<td>2.65</td>
</tr>
<tr>
<td>TimeGapP</td>
<td>4.05</td>
<td>8.37</td>
</tr>
<tr>
<td>TimeGapC</td>
<td>10.52</td>
<td>9.86</td>
</tr>
</tbody>
</table>

*Number of Observations: 17,942

**Preliminary Results**

Table 3 shows the estimation results for the logit model. Specifically, column (1) and (2) reveal the main results for WOM generation of Pepsi and Coca Cola respectively and column (3) and (4) show findings from two robustness checks of results for the Coca Cola WOM. Generally, our hypotheses are all supported and most results are consistent across both brands and their associated robustness checks.

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) GenP</th>
<th>(2) GenC</th>
<th>(3) Cluster University</th>
<th>(4) Exclude CpV=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Friendscount</td>
<td>0.0075(0.002)***</td>
<td>0.0072(0.006)***</td>
<td>0.0072(0.006)***</td>
<td>0.0071(0.006)***</td>
</tr>
<tr>
<td>NFriendsP</td>
<td>0.439(0.265)*</td>
<td>0.021(0.152)</td>
<td>0.021(0.176)</td>
<td>-0.0009(0.155)</td>
</tr>
<tr>
<td>NFriendsC</td>
<td>-0.374(0.135)***</td>
<td>-0.22(0.043)***</td>
<td>-0.22(0.043)***</td>
<td>-0.224(0.044)***</td>
</tr>
<tr>
<td>TimeGapP</td>
<td>-0.056(0.033)***</td>
<td>-0.063(0.017)***</td>
<td>-0.063(0.015)***</td>
<td>-0.061(0.017)***</td>
</tr>
<tr>
<td>TimeGapC</td>
<td>-0.098(0.031)***</td>
<td>-0.089(0.011)***</td>
<td>-0.089(0.011)***</td>
<td>-0.089(0.011)***</td>
</tr>
<tr>
<td>SNage</td>
<td>-0.0715(0.519)</td>
<td>-0.0542(0.226)</td>
<td>-0.0542(0.225)</td>
<td>-0.012(0.022)</td>
</tr>
<tr>
<td>Activity</td>
<td>0.137(0.08)*</td>
<td>0.214(0.04)***</td>
<td>0.214(0.05)***</td>
<td>0.214(0.04)***</td>
</tr>
<tr>
<td>Female</td>
<td>0.23(0.323)</td>
<td>0.28(0.132)**</td>
<td>0.28(0.145)**</td>
<td>-0.2632(0.13)</td>
</tr>
<tr>
<td>PtimeP</td>
<td>3.26(0.749)***</td>
<td>-0.191(1.175)</td>
<td>-0.191(1.55)</td>
<td>-0.193(1.17)</td>
</tr>
<tr>
<td>PtimeC</td>
<td>1.407(0.704)**</td>
<td>1.876(0.26)***</td>
<td>1.876(0.31)***</td>
<td>1.86(0.26)***</td>
</tr>
<tr>
<td>Location</td>
<td>included</td>
<td>included</td>
<td>included</td>
<td>included</td>
</tr>
<tr>
<td>Observations</td>
<td>17,942</td>
<td>17,942</td>
<td>17,942</td>
<td>17,516</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

As hypothesized, a user’s probability to generate WOM about brands is influenced by the number of friends on SNS. According to Table 3, the coefficient of the Friendscount is positive and significant, suggesting that the probability for a user to generate WOM about brands on the Superbowl show increases with the number of friends he or she has. This supports Hypothesis 1 and is consistent with our inference from the self-presentation theory.

In terms of peer exposure, coefficients for NFriendC are both significant and negative across all models, while the coefficients for NFriendP are not significant. In model (1), the result indicates that a user's
probability to generate WOM about Pepsi would decrease with the number of friends that have generated WOM about Coca Cola, which provides evidences for our social conformity hypothesis. Specifically, a user with one more friend generating WOM about Pepsi before would decrease a user’s probability to generate WOM about Pepsi by 0.1%. On the other hand, since the reward for self-representation by generating WOM about Pepsi is not as clear as Coca Cola (because Pepsi did not have a TV commercial on the Superbowl XLIV show), we do not observe a significant effect from the number of friends generating WOM about Pepsi in our model. On the contrary, $NFriendC$ has a significantly negative effect in model (2), which supports the self-presentation hypothesis: a user with one more friend generating WOM about Coca Cola before would decrease the probability to generate WOM about Coca Cola by nearly 0.3%. Nevertheless, the coefficient for $NFriendP$ in model (2) is not significant. The reason might be that apart from the social conformity effect, peer exposure to the Pepsi brand also shift users’ attention away from Coca Cola. In sum, we found evidences for both H2 and H3.

Not surprising, the coefficients of $TimeGapP$, $TimeGapC$ are negative and significant, indicating that effects of peer exposure from both competing brand and same brand fades away with time passing by. If the later a user is influenced by WOM about brands after the Superbowl show, he or she would have a less tendency to propagate this discussion since the overall attention for the Superbowl commercials decays with time and people would care less about it over time. Hence, Hypothesis 4 is supported.

Apart from our main independent variables, estimation results for control variables present some interesting findings. The estimation for variable Activity is significant and positive. It is not difficult to interpret that a more active user has a higher probability to generate WOM about the Superbowl brands after the show. $PtimeC$ and $PtimeP$, which account for users’ brand preference or interest, have a strong explanatory power in a user’s probability to generate WOM for each brand. Specifically, a user with intrinsic preference for a brand has higher probability to generate WOM about this brand after the Superbowl show. For Pepsi’s WOM, with respect to the marginal effect, a user generating WOM about Pepsi before show has nearly 1% higher probability to discuss Pepsi again after the show. We included two location dummies in our regressions and neither shows any significant effects.

Additionally, different methods are implemented to corroborate our model estimation results’ robustness. First, we cluster the standard error of model estimates at the university level, in order to account for potential systematic correlations in response to the Superbowl commercials across different universities. The result for Coca-cola WOM is shown in column (3). Second, we excluded those users whose Activity is zero from our sample because it can be inferred that these users may never return to the SNS during our observed time periods. Therefore, it is less insightful to investigate those users’ online behaviors. Hence, 426 users are eliminated and the estimation result is shown in column (4). Our results also remain stable after these robustness-check procedures.

**Conclusion and Future Plan**

In this study, we investigate consumers’ response to TV commercials and the subsequent impact from peer exposure on brand’s content diffusion in SNS. Specifically, we explore the impact from peer exposure on WOM generation about specific brands from both same brand and competing brand at the individual level. In sum, our empirical results reveal several notable findings. First, peer exposure results in lower tendency for a user to generate WOM about both the same brand and a competing brand due to self-presentation and conformity motivations. Second, the number of friends on SNS also has a positive effect that motivates a user to generate WOM over both brands. While this study has illustrated a few promising results, it is still a research-in-progress work and several plausible extensions are planned as follows.

First, in the current analysis, we consider only the incidence on whether a user has generated WOM over certain brands. Nonetheless, sentiments embedded in WOM are not accounted for in this study. It might be plausible that WOM with different sentiments expressed would have different social impacts. Therefore, one possible extension is to adopt text-analysis techniques in investigating different impacts from positive WOM, negative WOM and neutral WOM. Second, the network structure of the SNS is not included in our empirical analysis at this stage. However, consumers might respond in a heterogeneous manner to competing WOM if they are subjected to different network structures. Hence, one planned extension is to focus on samples from one university and add in other network indices calculated within the university boundary. Lastly, current preliminary analysis is based on cross-sectional data, which has limitations in controlling for unobserved heterogeneity. One possible alternative is to use panel data
analysis methods for the empirical analysis in order to account for unobserved individual user level heterogeneity.

References


