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What Products Do People Talk About and Why? How Product Characteristics and Promotional Giveaways Shape Word-of-mouth

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Report Summary

People often share opinions and information and word-of-mouth has an important impact on product success. But why are certain products talked about more than others? While research has focused on understanding the consequences of word-of-mouth, less is known about the behavioral processes that drive aggregate outcomes such as product adoption and sales. Similarly, research has considered how particular people may shape the diffusion process, but less attention has been given to how the products themselves may impact buzz.

Here, Jonah Berger and Eric Schwartz examine the psychological drivers of word-of-mouth, investigating how product characteristics and campaign giveaways determine which products people talk about. First, they analyze a dataset from buzz marketing campaigns to test their behavioral hypotheses. Second, they conduct a large field experiment to uncover the underlying process driving the findings in the first analysis.

Their dataset comprises everyday conversations from 335 buzz marketing campaigns covering a broad range of products (e.g., food, financial services, and movies). Berger and Schwartz use a hierarchical model of word-of-mouth, which simultaneously reflects underlying differences across people and products, so the behavioral hypotheses are tested with a flexible, heterogeneous model. Their findings include the following:

Products that are used more frequently are talked about more frequently (and by more people). For example, an increase in product usage of four additional times per week is associated with a 10% increase in WOM. Similarly, products that are cued more frequently by the surrounding environment are talked about more frequently (and by more people). In addition, cues drive the effect of product usage on WOM: when both cues and product usage are included in the model, cues remain a significant predictor of WOM, while weekly product usage is reduced to insignificance.

The effect of cues strengthens as campaigns progress. Compared to earlier in the campaign (e.g., the first quarter) the frequency with which a product is cued by the surrounding environment is more positively linked to WOM later in campaigns. This suggests that as more time elapses since people first experience or learn about a product, being cued by the surrounding environment becomes increasingly important in driving conversation.

Results provide no evidence that more interesting products are talked about more frequently over the multi-month period of each campaign. Interesting products may be talked about more right after people experience them, even if they do not receive more WOM overall.

Results provide mixed support for the utility of promotional giveaways in boosting WOM. Giving away the product itself is associated with a strong and significant increase in WOM. Sending consumers a full product to try is associated with a 34% increase in WOM. Sending consumers multiple copies of the free product, however, is not associated with any additional WOM. Giving away samples is associated with a marginal increase in WOM and this was driven by the quantity of the giveaway: more samples were associated with more WOM. Non-product extras are associated with only a moderate increase in WOM, and this was

driven by the quantity of the giveaway. Giving away coupons and rebates is not linked with more WOM.

In their second study, the authors sought to test whether the relationship between cues and WOM was truly causal. The experiment was run on 1,687 BzzAgents who participated in a campaign for Boston Market. It corroborated the results of the cross-campaign analysis; increasing the cues for a product, in this case linking it to a usage situation that some participants did not already associate it with, increased WOM.

Overall, the studies demonstrate the important role of triggers or stimuli in the environment in shaping word-of-mouth about a product. Products that are cued more frequently—either because they are used more frequently or brought to mind by a related stimulus—receive more WOM.

These results suggest that when designing products or marketing messages, marketers should take into account the structure of the surrounding environment. Marketers often think that only outrageous or surprising products are buzz-worthy, but these findings indicate that even seemingly mundane products can get lots of word-of-mouth if they are cued often.

Results also indicate that while promotional giveaways can be useful in boosting word-of-mouth, certain types of giveaways (i.e., the product itself) are more effective than others. The framework used here offers a first step for managers to run a cost-benefit analysis of promotional giveaways and the value of the resulting WOM.

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Word of mouth is frequent and important. Consumers often tell their friends about a great pair of shoes, complain about a terrible hotel stay, and gossip about a restaurant opening. Social talk generates over 3.3 billion brand impressions each day (Keller and Libai 2009), and affects everything from the drugs doctors prescribe (Iyengar, Van den Bulte, and Valente 2009) to the products consumers buy (Godes and Mayzlin 2009; Leskovec, Adamic, and Huberman 2007; Moe 2009).

But why are certain products talked about more than others? Some movies get a great deal of buzz while others go unnoticed. Some restaurants are the talk of the town while others never get discussed. Indeed, research suggests that 10% of consumer packaged goods account for 85% of the buzz (Niederhoffer, Mooth, Wiesenfeld and Gordon 2007). But what characteristics of products lead them to be talked about more?

Recent word-of-mouth research has focused on identifying its consequences, but little empirical work has actually examined the process itself, or what consumers talk about and why (Stephen and Lehmann 2009). Consequently, while it is clear that word of mouth affects things like product adoption and sales, less in known about the behavioral processes that drive these aggregate outcomes (Goldenberg, Libai, and Muller 2001). Further, though research has considered how particular people (e.g., influentials, opinion leaders, or social hubs; Goldenberg, Han, Lehmann, and Hong 2009; Godes and Mayzlin 2009; Katz and Lazarsfeld, 1955; though see Watts and Dodds 2007) or network structures (Watts 2002) shape the diffusion process, less attention has been given to how products themselves may impact buzz. Brown and Reingen (1987) note that, "enhanced understanding of social influence…may simply be obtained by examining which products or services consumers are more likely to 'talk about'" (p. 361), yet little work has answered this call. Some research even suggests that item characteristics may not matter at all, arguing that what gets passed along or becomes popular depends mainly on process of imitation rather than anything about the items themselves (Hahn and Bentley 2003; Salganik, Dodds, and Watts 2006).

There is also little evidence about how promotional giveaways affect word of mouth. Marketers have started trying to influence what consumers talk about, hiring word-of-mouth marketing companies to facilitate buzz (Godes et al 2005; Godes 2008; Godes and Mayzlin 2009). These firms design marketing campaigns where consumers are given free products, coupons, or other gifts in the hopes that they will talk more about the brand. But do such giveaways really encourage buzz? Further, how do these factors affect not only overall WOM volume, but also the number of people who talk about a product (reach) and how much they do so (frequency)?

This paper examines psychological drivers of word of mouth, investigating how product characteristics and campaign giveaways shape what people talk about. First, we analyze a unique dataset containing reports of actual, everyday conversations from over 300 buzz marketing campaigns. Most prior WOM studies have focused on a single product, but by looking across many campaigns covering a diverse set of products, we gain deeper insights into the drivers of word-of-mouth. The data are analyzed with a multilevel/hierarchical model of WOM, which simultaneously reflects underlying differences across people and across products, enabling the key behavioral hypotheses to be tested above and beyond a flexible, heterogeneous model. Second, based on both theory and the model results, we conduct a large field experiment with random assignment across various US cities. By directly manipulating the main psychological driver identified in the model, we test its causal impact on word-of-mouth.

Our research sheds light on the psychological processes behind word-of-mouth, and provides insight into how companies can design more effective buzz marketing campaigns (also see Godes et al. 2005). We find that (1) products that are cued more by the everyday environment, such as those that are used more frequently, are talked about more; (2) more interesting products do not receive more word of mouth over a multi-month period; (3) the relation between interest and talking is more positive soon after consumers learn about or experience products (i.e., its impact fades over time); (4) the effectiveness of promotional giveaways in boosting overall WOM is mixed at best, with certain types of giveaways (e.g., giving away the product itself) more strongly linked to increased WOM than others; (5) breaking WOM volume into reach and frequency provides additional insight into how product characteristics and promotional giveaways shape what people talk about.

The rest of the paper is structured as follows. We discuss potential drivers of WOM and draw on the behavioral literature to develop our hypotheses. Then we test these hypotheses across a large set of WOM campaigns and a field experiment. Finally, we discuss the theoretical and practical implications of this research.

Drivers of Word-of-Mouth

Rather than focusing on product categories (e.g., food or books), or attributes in the traditional sense (e.g. horsepower), we attempt to understand why people talk more about certain products by investigating the underlying psychological drivers (Moldovan, Goldenberg, and Chattopadhyay 2006). Psychological motivations play an important role in shaping WOM (Cheema and Kaikati 2010; Wojnicki and Godes 2008). Certain products may evoke more emotion or fit better with people's cognitive constraints, and to the degree these aspects are common across individuals, they should influence what is discussed (Heath, Bell, and Sternberg 2001; Kashima 2008; Schaller and Crandall 2004). People reported greater willingness to share urban legends, for example, that elicited higher levels of disgust (Heath, Bell, and Sternberg 2001).

One psychological factor that might influence whether people talk about a product is the amount of interest it evokes. Intuition suggests that people will talk more about an intriguing high-tech gadget, for example, than a boring breakfast cereal. More generally, popular perspectives suggest that things which evoke interest (i.e., novel, surprising, or unexpected things) will receive more discussion (Dichter 1966; Rosen 2009).

But do interesting products or experiences *actually* get more word of mouth? Though the notion may seem intuitive, there are a number of reasons to question its validity. First, self-enhancement motives may lead people to *think* they will talk about more interesting products even if they do not actually do so (see Wojnicki and Godes 2008 for a discussion self-enhancement motives and WOM). Most people want to view themselves as somewhat interesting, and conversation topics can act as self expression. Consequently, if asked what they would talk about, people may be motivated to report that they will talk more about interesting rather than boring things even if that is not what actually occurs. Second, though motivation may drive what people talk about in some situations (e.g., bringing up interesting topics to look good on a date), most day-to-day conversations may resemble idle chatter about whatever normal everyday things happen to come to mind (Keller Fay Group 2006). While technology or media and entertainment are probably more interesting, for example, prior work suggest that food and dining (i.e., consumer packaged goods) are more frequently discussed (Keller and Libai 2009). Consequently, though interesting things may be talked about more in a few instances, this may be overwhelmed by the preponderance of situations where people talk about anything that happens to come to mind, interesting or not. Third, while more interesting things may get slightly more WOM right after they are experienced, they may not get more WOM over a longer time horizon. Characteristics of stimuli like interest, novelty, and originality fade over time (Moldovan, et al. 2006; Wu and Huberman 2007). Consequently, while interest may help predict buzz right after people first experience or learn about a product, it is less likely to be a strong predictor of ongoing buzz. Overall, given the lack of empirical evidence addressing this issue, we explore whether more interesting products receive more WOM.

Since conversations may be driven by whatever comes to mind, we also examine the role of cues in shaping word of mouth. Consumers may find a product interesting, but if they are not reminded to think about it, they may not discuss it. Cues in the environment, however, can shape product accessibility (Lynch and Srull 1982; Nedungadi 1990). Products should be more accessible if they are used more frequently, for example. Therefore, one example of an environmental cue is a product usage occasion. Indeed, one reason food and dining may be frequently discussed is because people are reminded to think about food multiple times a day (i.e., every time they eat). More broadly, conceptually related cues can also bring products to mind (Collins and

Loftus 1975). Reese's Pieces and orange soda were more top of mind in times of year when there were more cues related to the color orange in the surrounding environment (i.e., Halloween in Berger and Fitzsimons 2008). Consequently, to the degree that certain products tend to be cued more across individuals, because they are used more often or just cued more generally, they should be talked about more.

While we focus on product characteristics and psychological drivers, we also examine how aspects of word-of-mouth campaigns themselves shape WOM (also see Biyalogorsky, Gerstner and Libai 2001; Ryu and Feick 2007). Most campaigns involve sending consumers promotional giveaways to encourage them to talk about the product. Participants in a Tabasco campaign, for example, were sent a bottle of the hot sauce to try. Consumers may also receive free samples (e.g., mini tube of toothpaste), coupons or product rebates, or extras such as brochures, postcards, or stickers. The prevalence of such giveaways suggests that firms believe they are effective. More than half the campaigns conducted by a major buzz marketing firm between August 2002 and January 2009 included a free product and nearly half included some sort of non-product extra (Table 1, Panel B, following References). Further, consumers are often sent multiple copies of the same promotional item and encouraged to pass along to their friends. Of campaigns that included coupons, for example, 77% provided more than one. But while sending consumers promotional items is a common practice, no work we are aware of has examined which of the various types of giveaways, if any, are linked to increased WOM.

Finally, we not only examine how product and campaign characteristics affect overall word of mouth volume, but also the specific way in which they do so. Companies hiring buzz firms essentially are buying spots in a new medium (e.g., conversations), and traditional media metrics like reach and frequency are no less relevant than they are for print, radio, TV or Internet (Agostini 1961; Rossiter and Danaher 1998). While such measures typically refer to receiving messages (e.g., audience exposure), we consider these measures for the senders of WOM. How do product characteristics and campaign giveaways affect the number of people who talk about a product (reach)? Among the people who do talk, how do these factors influence how much they do so (frequency)? The decomposition of overall WOM volume into reach and frequency has important implications for the consequences of word of mouth. More people talking about a product (reach), for example, should broaden WOM dispersion (Godes and Mayzlin 2004) and increase the chance that different communities learn about the product, extending awareness and potentially boosting purchase likelihood. Thus we investigate how product and campaign characteristics affect how whether an individual talks or not (reach), and among those talkers, how many conversations they have (frequency).

The Current Research

Building on the preceding discussion, we explore a number of key research questions:

- Are more interesting products talked about more frequently in general?
- Are products that are cued more by the surrounding environment talked about more often? For example, are more frequently used products talked about more and is this driven by cueing?
- Are promotional giveaways (e.g. free products, samples, and coupons and rebates) linked to increased word of mouth, and if so, which ones? Does giving away more of a particular item have any additional effect?

- How do these factors predict the reach and frequency of word of mouth?

We investigate these questions in two ways. First, we look at WOM across a variety of buzz marketing campaigns to examine the link between product characteristics, as well as campaign giveaways and WOM. Second, we use the results of this analysis to inform the design and implementation of a field experiment, testing whether the key product characteristic linked to WOM (i.e., cues) has a causal influence on buzz.

A Cross-Campaign Analysis of Buzz

Our first study uses a unique dataset to examine how product and campaign characteristics impact buzz. Our data focuses on 335 word-of-mouth marketing campaigns covering a broad range of products (e.g., food, financial services, and movies, Table 1C, following References). The data includes information about each product, the campaign itself (i.e., whether free products or coupons were given away), and how much each individual in each campaign talked about the product.

The data were provided by BzzAgent, a marketing company which helps generate WOM for its clients (see Godes 2008; Godes and Mayzlin 2009). They maintain a large database of people ("agents") who are interested in learning and talking about new products. These individuals participate on a volunteer basis. Clients approach BzzAgent with a product they would like to create buzz around. Then based on the geographic and demographic specification of the client's target audiences (e.g. "women in Chicago"), BzzAgent invites the appropriate agents to participate. Agents are not required to talk about the product, or say positive things. They are simply asked to report when they share WOM about the product.

Each campaign runs for several weeks.[1] Agents who have volunteered to participate are sent a package of materials. This contains information about the product as well as promotional giveaways that vary across campaigns, such as free products, rebates, or gifts. All agents in the campaign receive the same materials. Agents also receive emails throughout the campaign with additional information and reminders to share WOM. Agents file reports about each incidence of WOM through a simple website, and the number of reports filed by a given agent in a given campaign serves as our key outcome measure (see Godes and Mayzlin 2009; Cheema and Kaikati 2010).[2]

Campaigns differ in size. The middle 50% of all campaigns involved between approximately 1,000 and 5,000 agents. Only about 10% of campaigns had more than 10,000 agents, and only about 15% included fewer than 1,000 agents.[3]

The median number of campaigns each agent participated in is three campaigns, but there is a great deal of variability since about 25% of agents participated in only one campaign and 10% participated in more than 13 campaigns. Agents included in the data participated in at least one campaign between August 2002 and January 2009. Participation means that an agent completed a pre-campaign survey and logged into the BzzAgent website at least once during the campaign. Importantly, participation does require talking about the product. An agent may participate but end up submitting zero reports. One report is considered equivalent to one conversation.

For the purposes of this analysis, we take a stratified sample by taking a uniform sample of 2,000 agents and using all of the campaigns in which those agents participated.

This yields nearly 11,000 observations, where each observation is how many conversations that agent had in that campaign (that is, the agent-in-campaign level). It was important to sample in this manner since there is substantial variability in the number of agents in each campaign and the number of campaigns in which each agent participated. The histogram in Figure 1 (following References) summarizes the data pooled across all campaigns and all agents, so it indicates how frequently each number of conversations occurs across all of the agent-in-campaign observations. The count data are skewed towards zero, with 43% of all observations being zeros (i.e., no conversations were reported by a given agent in a given campaign). The median number of conversations is one, and 90% of all observations are four conversations or fewer. Statistically, this follows a very common pattern of over-dispersed count data. The histograms for each individual campaign follow the same shape as this aggregate histogram across campaigns. At the observation level, reach is whether or not an agent talks at all about a product in a campaign, and frequency is, given an agent talks, how many conversations she has.

Key independent measures

Each product characteristic was quantified by a different set of three independent raters (see Heath, Bell and Sternberg 2001 for a similar approach). They were given a list of the products (e.g., Kellogg's Smorz Cereal, Ralph Cool perfume, the book *Unstuck*) and a brief description of each. Those who rated *product usage* were asked "How many times per week is this product typically used?" Those who coded *cue frequency* were asked "How frequently might the surrounding environment cue or remind people to think about the product? (1 = not at all, 5 = a great deal). Those who coded *interesting* were asked "How interesting is this product?" (1 = not at all, 5 = a great deal). Coding was done at the product level and participants coded each product individually (e.g., "How interesting do you find Ralph Cool perfume" or "How many times per week do you use Kellogg's Smorz Cereal"). In all cases, coders were asked to rate the products from the perspective of a potential customer for whom the product is intended (e.g., make up for women). Inter-rater reliability was high (weekly usage $\alpha = 0.91$; cues $\alpha = 0.83$; interesting $\alpha = 0.79$)[4] and the scores were averaged across coders for each dimension. See Table 1, Panel A for more details on these measures of product characteristics.

We also recorded the promotional giveaways sent to the agents. BzzAgent provided full information about what agents received in each campaign, such as the product, samples, coupons or rebates, and non-product extras (e.g., stickers). We noted the presence and number of each type of item agents received (Table 1, Panel B for details). See Table 2 (following References) for correlations among the independent variables.

Model development

We explicitly model WOM at the individual level, where y_{ij} represents the number of conversations an individual agent i reported during campaign j for a particular product. The data structure could be considered a jagged contingency table of counts: agents participate in different numbers of campaigns, and campaigns differ in number of agents participating. In addition, agents are not fully nested within campaigns. It is important to differentially weight the data from individuals and campaigns based on how many observations we have for each, and our approach does just this. [5] The model used is a Poisson log-normal model, which is a type of generalized linear mixed effects models (see Appendix for a discussion of model fit and the rationale for choosing this approach). Each observation y_{ij} has an unobserved Poisson rate of conversations, λ_{ij} . This rate parameter, or the expected number of conversations, is a log-linear combination of the global mean μ, each individual agent's unobserved talking propensity α_i, each product-campaign's unobserved propensity to be talked about δ_j, the product-campaign's observed covariate vector X_j, the coefficient vector β, and each observation-specific unobserved error ε_{ij} . Formally,

$$y_{ij} \sim \text{Poisson}(\lambda_{ij})$$

$$\log(\lambda_{ij}) = \mu + \alpha_i + \delta_j + X_j\beta + \varepsilon_{ij} ,$$

where the slopes of the observed predictors, the components of β, are common across all agents and campaigns, but the parameters α_i , δ_j , and ε_{ij} are random effects. These parameters vary across agents, campaigns, and observations, respectively, and they are independently distributed as follows:

$$\alpha_i \sim N(0,\sigma_\alpha) \ , \ \delta_j \sim N(0,\sigma_\delta) \text{, and } \varepsilon_{ij} \sim N(0, \sigma_\varepsilon),$$

where those random effects are uncorrelated with one another. The parameter σ_α reflects the degree of unobserved heterogeneity across individuals, and σ_δ reflects the degree of unobserved heterogeneity across campaigns (not accounted for by observed covariates X_j). The observation-specific idiosyncratic error can be interpreted as the unobserved interaction effect of a particular person's propensity to talk about a particular product-campaign. The parameter σ_ε reflects the degree of over-dispersion in the counts, conditional on the other parameters. As in random effects models, we assume the observed predictors are uncorrelated with the random effects. To investigate our questions we examine the components of the coefficient vector β representing the associations of each product characteristic and campaign giveaway with WOM.

By including different sets of variables in the model, and using disaggregate data at the level of an agent-in-campaign, we estimate multilevel models to test which product characteristics and campaign giveaways are linked to overall WOM. By looking at models examining overall WOM, reach, and frequency, we can also gain deeper insight into how the WOM is occurring. The Frequency model is a count (Poisson-based) model, but the Reach model is a binary choice (binomial-based) model, using a logit link instead of log link relating the linear predictor to the outcome. [6]

Results and discussion

Product characteristics. [7] As shown in Table 3 (following References), not surprisingly, products that are used more frequently are talked about more (Model 3.1). Parameter estimates indicate that a one standard deviation increase in product usage (i.e., four more times per week) is associated with a 10% increase in WOM, or approximately 13 extra conversations per 100 people (based on the average campaign with 130 conversations per 100 agents, holding all other predictors constant).

More importantly, Model 3.2 illustrates the importance of cues in driving both this effect, and WOM more generally. First, products that are cued more frequently by the surrounding environment are talked about more frequently. A one-standard deviation increase in the frequency of being cued is associated with a 19% increase in WOM, or an extra 25 conversations per 100 people for the average campaign. Second, cues drive the effect of product usage on WOM: when both cues and product usage are included in the model, cues remains a significant predictor of WOM while weekly product usage is reduced to insignificance. A mediation test for multilevel models confirms the hypothesized pattern of mediation ($t = 6.20$, $p < 0.0001$; see Appendix for a discussion of meditational analysis for multilevel models and convergent evidence from the linear model on aggregate data). Using a product more leads it to come to mind more often and thus be talked about more. Decomposing this into the impact on reach and frequency shows that cues are related to both: products that are cued more often are talked about by a greater number of people (Table 4, Reach, following References), and the people who do talk mention the product more frequently (Table 4, Frequency, following References).

Model 3.3 examines the relationship between interest and WOM (Table 3). Results provide no evidence that more interesting products are talked about more frequently over the multi-month period of each campaign. [8] This finding is not driven by the specific way we measured interest as other ways of measuring the construct and related constructs yield the same result. First, we had a broader set of individuals (N = 80, mean age = 42) rate how interesting ("How interesting do you find this product?") or original ("How original do you find this product?") the products were on 1-5 scales. Neither measure, however, was linked to WOM. Second, we had research assistants use 1-5 scales to rate the products on related constructs, i.e., how surprising ("How surprising do you find this product?") or how novel ("How novel is this product?") they were. Neither measure, however, was linked to increased WOM. The persistent lack of relationship across measures and rater populations underscores the notion that more interesting products may not receive more buzz overall.

To further test our measure of interest, we examined whether it would predict intentions to spread WOM (1 = not at all likely, 5 = extremely likely). Each participant was given a random set of 50 products to avoid fatigue and ratings for each product were averaged across participants. Results indicate that our measure of interest was significantly related to intent to share WOM. People reported greater willingness to talk about more interesting products ($r = .22$, $p < .001$).[9] There was no significant relationship, however, between willingness to talk and either product usage ($r = -.04$, $p > .40$) or frequency of being cued by the environment ($r = .02$, $p > .70$). Further, when all three of these factors were included in a multiple regression predicting WOM intentions, how much interest the product evoked remained a significant predictor ($\beta = 0.19$, $t = 4.86$) but people did not report any greater likelihood of talking about products that are used ($\beta = -0.01$, $t = 1.03$), or cued more frequently ($\beta = 0.05$, $t = 1.52$).

These relationships further support the validity of our interest measure. They are also consistent with the notion that people may think they will talk more about interesting products, even though they may not actually do so. Finally, the lack of relationship between cues and WOM intentions suggests that people may not be aware of the role of cues in shaping what they discuss.

Ancillary analyses also support our suggestion about the temporal relationship between interest and WOM. As noted earlier, while people may find a product original or interesting when they first experience it, these feelings fade over time (Moldovan et al 2006). Consequently, the effect of interest on WOM should likely dissipate over the length of the campaign. Our results are consistent with this suggestion. Given the campaigns already occurred, it is impossible to go back and measure how interest in each product changed over time. We can, however, examine how our interest measure predicts WOM at different points in the campaign. We allow the slope to vary to test if the impact of interest on WOM is different early versus late in the campaign.

Consistent with our theorizing, while there is a positive relationship between how interesting products are and buzz in the first fourth of the campaign ($\beta = 0.03$), for example, this relationship dissipates over the latter three-fourths (interest x time interaction; $\beta = -0.08$, $t = -2.62$).[10] The pattern of results is robust to the different ways of splitting the campaign into early and later periods (e.g., first third, fifth, or tenth of campaign). This significant interaction suggests that interesting products may be talked about more right after people experience them, even if they do not receive more WOM overall. Further it bolsters the notion that our failure to find an association between interest and ongoing WOM was not due to a poor measure of interest.

Data on how cues relate to conversations over time is also consistent with our overarching framework. Rather than dissipating, the effect of cues strengthens as campaigns progress. Compared to earlier in the campaign (e.g., first fourth), the frequency with which a product is cued by the surrounding environment is more positively linked to WOM later in campaigns (cues x time interaction; $\beta = 0.08$, $t = 4.13$). The pattern of results is robust to the different ways of splitting the campaign into early and later periods (e.g., first third, fifth, or tenth of campaign). This suggests that as more time elapses since people first experience or learn about a product, being cued by the surrounding environment becomes increasingly important in driving conversations.

Campaign giveaways. Two models address the effect of promotional items on talking. We consider Model 4.1 which includes the quantity (0, 1, 2, etc.) of each type of giveaway that was included in a campaign (Table 4). By running Model 4.2, which also includes variables for the presence or absence (1 or 0) of each giveaway, we examine whether giving away more of a certain item is associated with additional word of mouth, above and beyond the mere presence of that type of item in the campaign. Additionally, not all products can be sent in the mail (e.g., it is easy to send a book, but hard to mail a Taco Bell meal or a Dodge truck)[11]. Consequently, we consider the effect of giving away a product controlling for whether it could be realistically mailed to an agent.

Results provide mixed support for the utility of promotional giveaways in boosting word of mouth (Table 4). Giving away the product itself is associated with a strong and significant increase in word of mouth (Model 4.2). Sending consumers a full product to try is associated with a 34% increase in WOM, or equivalent to an extra 43 conversations per 100 people. Sending consumers multiple copies of the free product (i.e., more than one), however, is not associated with any additional word of mouth (Model 4.2). Decomposing these effects into the impact on reach and frequency shows that giving away a free product is related to both: it is associated with a greater number of people talking about the product and the talkers speaking more frequently (Table 4).

Evidence was weaker, however, for the link between word of mouth and other promotional giveaways. Giving away samples was associated with a marginal increase in word of mouth (Model 4.1), and this was driven by the quantity of the giveaway: more samples were associated with more word of mouth (Model 4.2). A one standard deviation increase (i.e., sending consumers 10 additional samples), for example, is associated with

15 additional conversations per 100 people. Decomposing this into the impact on reach and frequency shows that giving away more samples is related to reach but not frequency: it is associated with a greater number of people talking about the product but not the talkers speaking any more frequently (Table 4).

Evidence was even weaker for non-product extras. They were associated with a moderate increase in word of mouth (Model 4.1), and this was driven by the quantity of the giveaway: giving away more extras was associated with more word of mouth (Model 4.2). A one standard deviation increase (i.e., giving away 7 more extras) is associated with 9 additional conversations per 100 people. It is worth noting, however, that the effect of extras becomes non-significant when two campaigns with the largest number of extras are removed ($\beta = 0.0002$, $t = 0.03$). We leave these points in the analysis because (a) theory of diagnostics of outliers and influential points is less clear for multilevel generalized linear models than linear models and (b) each value represented many observations and was a naturally occurring numbers of giveaways. Removing extreme values does not change coefficients for any other independent variables. Decomposing the impact of extras into its link with reach and frequency shows that giving away more extras is marginally related to frequency but not to reach: it does not lead any more people to talk, but those who do speak may talk slightly more frequently (Table 4).

There is also mixed evidence for the link between giving away coupons and rebates and WOM. Neither their presence nor quantity is linked to more word of mouth overall (Model 4.1, 4.2). Further, they are not associated with more conversations among the people that do talk (Table 4, Frequency). However, there is a significant link between this factor and whether or not an agent talks (Table 4, Reach). Including coupons or rebates in a campaign is associated with more people talking, with more coupons or rebates associated with an increase in the number of people that talk.

Potential limitations

Selection oriented explanations (whether at the level of agents, campaigns, clients, or BzzAgent) have difficulty accounting for these results.

First, one could argue that BzzAgent only offers campaigns to agents who are most likely to talk about that product. Second, one could argue that agents self-select into campaigns in which they will talk a lot about the product. Discussions with BzzAgent, however, cast doubt on these possibilities. BzzAgent has an allocation engine that satisfies its clients' requests that campaigns focus on geographic regions and other constraints (e.g., gender or having children).[12] Thus, rather than the quickest or most interested agents gaining access, almost all agents in a region are encouraged to join. Often, this fills the campaign quota. If there is still room, BzzAgent prioritizes people who have not done a campaign in a while, making it less likely that people with high propensities to buzz self-select into any campaign of their choice.[13] In addition, if the best agents were getting into campaigns first, average WOM per agent should then be lower in larger campaigns, as worse agents would need to be included to fill the quota. This is not the case, however. There is no correlation between the number of agents in a campaign and average WOM per agent ($r = -0.01$, $p = 0.90$). Finally, even if these biases did exist, they would boost overall talking levels across campaigns but not bias our coefficients of interest, which depend on differences across campaigns.

To be a true concern, selection would have to be correlated with our suggested drivers of WOM. Though selection seems plausible for some product characteristics, it makes less sense for the ones we find to be significantly associated with WOM. It is possible agents may pick campaigns based on whether they anticipate the products to be interesting, but it is less likely most agents would consider how often a product is cued by the environment when picking campaigns.

Third, one could argue that clients strategically hire BzzAgent only if they think a campaign will boost WOM, so only easy to talk about products would be in the data. But the reverse is also possible: firms only hire BzzAgent if their product is not getting enough WOM naturally, so the dataset contains many products that are difficult to talk about. Either way, this selection would shift in the average WOM across products but does not explain how WOM varies with product and campaign characteristics.

Fourth, one could argue that clients only give away their product when they anticipate that trial will increase WOM (i.e., perhaps when the product is interesting). That is, the design of a campaign is endogenous to campaign success. A number of points, however, cast doubt on this possibility. To start, more interesting products are not any more likely to be given away ($r = 0.02$, $p > 0.20$; see Table 2). Additionally, discussions with BzzAgent indicate that rather than being driven by what clients thought would increase WOM, variation in giveaways was driven by clients wanting to save money or not having products available to share. Finally, this argument should hold for all giveaways (not just the product), but the data do not show this.

Summary

Examining hundreds of word-of-mouth campaigns provides insight into how product and campaign characteristics shape WOM. Products that are cued more, whether through product usage or otherwise, are talked about more frequently. More interesting products do not generate more WOM over the multi-month campaigns. Ancillary results, however, suggest that interesting products may get more WOM right after consumers learn about the product.

These results are particular interesting given they diverge from consumer expectations. People thought they would talk more about interesting products but did not think they would talk more about products that were cued more frequently. This disconnect illustrates that WOM intentions may not always be accurate, particularly in cases where consumers are unaware of the factors that shape their behavior (e.g., subtle cues in the environment) or where lay theories (i.e., that people talk about more interesting things) may not actually be correct.

The effects of promotional giveaways were mixed. Results suggest that sending people a free product is strongly associated with increases in both the number of people that talk and how frequently they do so, but sending additional products has little added benefit. The other effects were weaker. Coupons and rebates are linked to an increase in the number of people that talk, with more of them (e.g., share with a friend coupons) having an additional effect, but they do not predict how frequently people talk or the overall amount of word of mouth. Number of samples is weakly associated with overall buzz, and that appears to be driven by their association with the number of people who talk, but they do not lead people to talk more. The number of extras also has a small relationship on overall buzz, and while they do not seem to get more people to talk, they are related to the frequency with which the talkers talk.

Field Experiment

The breadth of products and categories used in the cross-campaign analysis speaks to the generality of the findings, but one may still wonder whether the relationship between cues and WOM is truly causal. Consequently, we also conducted a field experiment; the design was informed by both our prior theorizing and the results of the observational analysis. Specifically, we test whether manipulating the significant psychological factor linked to WOM in the observational data (i.e., how frequently the product is cued) affects WOM.

We examine whether linking the brand to an additional cue in the environment increases WOM. One way to increase product accessibility is to increase the frequency of existing cues but another is to create new links to stimuli with which the product was not already associated. For example, linking a reminder to eat fruits and vegetables to an object in dining halls increased fruit and vegetable consumption by encouraging people to think about the reminder more (Berger and Fitzsimons 2008).

We manipulated cues by manipulating the messaging different participants received during a BzzAgent campaign for the restaurant chain Boston Market. Half the agents received a message linking the product to a particular cue (dinner), while the other half received a control message. We also measured participants' prior associations between the brand and that cue to directly test whether cueing is driving any observed effects. While some consumers (strong dinner associates) already associate Boston Market with dinner, others (weak dinner associates) do not. Consequently, while thinking about dinner should already bring Boston Market to mind among strong dinner associates, it should not naturally come to mind among weak dinner associates.

We predict that messages which associate the chain with dinner should have a differential effect on consumers based on their existing product associations. The dinner manipulation should be more likely to boost product accessibility among weak dinner associates (because strong dinner associates already associate the brand with dinner), and consequently, it should be more likely to increase the frequency with which they talk about the brand. Thus, we predict that the effect of message should be moderated by participants' existing product associations. Among people who do not already associate the chain with dinner, the dinner message will boost WOM.

Method

The experiment was run on 1,687 BzzAgents who participated in a campaign for Boston Market. We measured existing product usage associations prior to the start of the campaign. Agents complete a pre-campaign survey with various campaign-related questions at the beginning of every campaign. In addition to the standard questions, we added a question which measured how much participants associated the product with dinner ("Boston Market is a dinner place," 1 = strongly disagree, 7 = strongly agree). Participants were stratified into three groups based on their responses to this measure (1-3 = low, 4 = middle, 5-7 = high). Within each stratum, participants were randomly assigned to one of our two experimental conditions.

We manipulated the focus of the email messages BzzAgents received during the first six weeks of the campaign. Every two weeks during each campaign, agents receive emails with product information and reminders to file WOM reports. We modified the content of the messages to test our underlying hypothesis. Half the agents received control messages, while the other half received messages that linked Boston Market to dinner. For example, for participants in the control [dinner] condition, the subject line of the first email read "Thinking About A Place to Eat [Thinking About Dinner]? Think About Boston Market!" (see Appendix for the full text of the email update). The association between Boston Market and dinner was mentioned 19 times across the three email updates (compared to zero in the control condition). All other information between conditions was identical.

Results

Data were analyzed using a hierarchical model similar to the one used in the cross-campaign analysis. Since we focus on a single campaign, there are just two levels, agent specific parameter heterogeneity and the idiosyncratic observation error. This model assumes that conditional on each individual's unobserved propensity for talking, experimental condition, and dinner association, the number of conversations is an over-dispersed count following a Poisson log-normal distribution.

As predicted, broadening the potential set of cues for the product increased word-of-mouth (Figure 2, following References). There was a significant message x pre-existing product association interaction ($\beta = -0.067$, $t = -2.15$). Consistent with our prediction, decomposition of the interaction one standard deviation above and below the mean product association shows that while there was no effect of the message for participants who already strongly associated Boston Market with dinner ($\beta = -0.018$, t = -

0.28), it did have an effect among participants who did not associate the chain with that usage situation. Among these people, the dinner message significantly increased WOM ($\beta = 0.175$, $t = 2.74$).

Stated another way, while the control condition shows that participants with stronger pre-existing dinner associations naturally tended to talk about the brand more ($\beta = 0.068$, $t = 2.90$), the dinner message reduced this discrepancy. In the dinner condition, participants with low pre-existing dinner associations now talked about the brand as often as participants with high pre-existing dinner association ($\beta = 0.001$, $t = 0.04$).[14]

Discussion

The field study corroborates the results of the cross-campaign analysis; increasing the cues for a product, in this case, linking it to a usage situation that some participants did not already associate it with, increased WOM. Among participants who did not already associate Boston Market with dinner, linking the product to that cue led them to talk more about the brand. This moderation demonstrates that these effects are driven by cueing rather than a particular message just happening to be more effective overall.

The interaction in these results can be seen as similar in flavor to the findings that weaker brands get more of a lift out of referral rewards (Ryu and Feick 2007), and that in the context of buzz marketing campaigns, WOM from less loyal consumers is more effective at generating sales (Godes and Mayzlin 2009). Weaker brands likely get more lift because stronger brands are already discussed, and less loyal customers likely boost sales more because more loyal customers have already talked to their friends. Similarly, as predicted, our manipulation had stronger effects among people who did not already associate the product with the cue because people who did already have that link likely already share WOM upon exposure to the cue.

Consistent with the cross campaigns analysis, cues not only increased overall WOM but also got more people to talk about the brand in the first place (i.e., reach). We examined the effect of dinner association and our manipulation on whether people talk or not. This reach model, much like the overall WOM model, yielded a significant interaction ($\beta = -0.078$, $t = -2.30$). This underscores the notion that manipulating cues not only increases overall WOM, but it does so by extending its reach.

General Discussion

Word-of-mouth is frequent and important. Social transmission can significantly affect consumer choice and sales, and as a result, word of mouth campaigns have become a standard part of many companies' marketing plans. But while it is clear that consumer conversations impact product success, relatively little is known about why certain products are talked about more than others. Further, while companies often give away promotional items to encourage consumers to talk, little is known about the effectiveness of such giveaways. Consequently, while it is clear that word of mouth has important consequences, less is known about (1) the behavioral processes that drive these outcomes and (2) how companies can design campaigns to increase word of mouth.

This research addresses both these issues. Analysis of over 300 buzz marketing campaigns, as well as a field experiment using random assignment provides insight into how product characteristics and campaign giveaways drive WOM. Products that are cued more frequently by the environment, whether by being used more often or otherwise, are talked about more. Further, while we find little evidence that more interesting products receive more WOM overall, the data suggest that interest may predict how much people talk about a product right after they experience or learn about it. Thus, taken together the results suggest that at least in the face to face WOM context examined here, what people talk about is driven by what comes to mind. Cueing by the environment is particularly important in driving ongoing conversations, and it appears to shape both the number of people who talk and how much they do so. More broadly, by combining empirical analysis of hundreds of products across dozens of categories with a field experiment we bolster the generalizability of the results while underscoring the causal role that cues play in increasing WOM.

In addition, our results suggest that promotional giveaways can be useful in boosting word of mouth. That said, certain types of giveaways seem more effective, both overall, and in generating reach and frequency. Giving away the product itself had the largest effect, and appeared to boost both the number of people who talk and the frequency with which they do so. The effects of the other giveaways were more mixed. From both a managerial and psychological perspective, our analyses point to the importance of decomposing word of mouth into frequency and reach. These metrics have been shown to be useful in understanding media spending, and by not decomposing the outcome into these two dimensions, we may be missing key drivers of WOM.

Overall, this research shows the benefits of drawing on behavioral theory and statistical analysis of observational data to inform a randomized experiment in the field. By mapping theory and findings onto the design and implementation the experiment, we further investigate the causal mechanism driving the observed findings, enhancing both the contributions to theory and marketing practice.

Managerial implications

When designing products or marketing messages, our results suggest taking into account the structure of the surrounding environment. Marketers often think that only outrageous or surprising products are buzz-worthy (Dye 2000), but our findings indicate (1) people do not recognize the role that cues may play in shaping WOM and (2) that even seemingly mundane products can get lots of word of mouth if they are cued often. By not only considering whether something will grab people's attention, but also whether it will be triggered by the surrounding environment, managers can increase the chance their products come to mind, which will increase WOM (as well as choice and sales, Berger and Fitzsimons 2008; Nedungadi 1990).

Our results suggest that giveaways vary not only in overall effectiveness, but also how they shape WOM reach and frequency. Consequently, managers should carefully consider which of these outcomes they care about most. Reach should be particularly useful when awareness drives sales, for example, as more people talking about the product should increase the dispersion of word of mouth, which should increase product success (Godes and Mayzlin 2004). Increased frequency, on the other hand, may help generate brand evangelists. Further, given that two people talked to by one person are more likely to themselves be connected than two people talked to by different people, boosting frequency could also help foster brand communities.

Whether giveaways are cost effective, however, depends on their cost and the value of WOM. As noted earlier, giving away a product is associated with an additional expected 43 conversations per 100 people, on average. If we assume that 10 conversations convert to even just one additional purchase, then as long as the cost of mailing the product is less than four times its price, it is worth sending out a free product. While precisely assigning a dollar value or the ROI of each buzz marketing campaign element is beyond the scope of our data, the framework we use here should be considered the first step for researchers and managers to run such a cost-benefit analysis.

These findings may also be useful in explaining relationships between buzz and other factors. Both purchase rates and advertising budgets, for example, appear to be positively correlated with word of mouth (Niederhoffer, et al. 2007). While many things could explain these relationships, they are consistent with our cue-based approach. Products that are purchased more often, or seen more often in advertisements, should be more accessible, and thus, talked about more. While advertising and WOM are often seen in opposition, they may actually be quite complementary (Keller and Libai 2009). In addition to its direct benefit on sales, advertising may also have an indirect effect through increasing WOM.

Limitations and future research

While some of the aspects we study here (i.e., promotional giveaways) may be restricted to WOM campaigns, there is no reason to believe that the psychological drivers which lead product characteristics to affect WOM, or make giveaways more effective, should not also hold more generally. People who participate in buzz marketing campaigns may be more talkative than most, but regardless of any main effect, things like cues should have similar effects among the rest of the population. Indeed, prior research shows that WOM from agents in buzz marketing campaigns is similar to WOM from regular individuals on a number of dimensions (Carl 2006), as is the WOM that agents share whether they are in campaigns or not (Carl and Noland 2008).

With better individual level data, future work might examine the role of individual heterogeneity in psychological drivers of buzz. The high degree of reliability across the people rating our product characteristics suggests that there is a good degree of overlap in what different people find interesting and cued by the environment. The fact that these aggregate product- and campaign-level measures were related to buzz suggests that these shared psychological aspects are useful in predicting collective outcomes. There is certainly some variation, however, in what people find interesting or how often they are cued. The retrospective nature of our analysis (i.e., most campaigns occurred years ago) makes it impossible to get real-time ratings of each product from each campaign participant, but doing so, particularly over time, would yield even more precise estimates of the various drivers of buzz. This would also shed light on how much individuals perceive different levels of each product characteristic (i.e., value of variable) versus having different importance weights (i.e., coefficient) on what drives them to talk.

Though we did find any evidence that more interesting products receive more WOM overall, this does not mean that interest (or other factors like surprise, novelty, or originality) have no link to what is discussed. Indeed, our results provide some suggestion that more interesting products may be talked about more right after people experience them (also see Moldovan et al. 2006). Future work might examine more directly when interest does and does not shape word of mouth.

The factors examined here are by no means the only product aspects linked to WOM. Consumers may talk more about products that have higher perceived risk or uncertainty (Van den Bulte and Wuyts 2007), to collect information or reduce their unease. Visible products or those used in public rather than private may generate more WOM because their physical presence acts as a cue to remind people to talk about them. Further, while our analysis focused on whether people talked about a product, future research might also examine how product and campaign characteristics affect other outcomes (e.g., the quality of conversations or whether those conversations translate into sales). More interesting products, for example, may generate longer conversations.

One particularly rich area for further investigation is offline or face-to-face word of mouth. Researchers often use online conversations, reviews, or content transmission to study WOM (Berger and Milkman 2009; Godes and Mayzlin 2004; Moe 2009), but given that most WOM occurs face-to-face (76%, Keller and Libai 2009) this area deserves more attention.

This is particularly true given the potential differences between face-to-face and online transmission (see Godes et al 2005). One potential difference may be the threshold for discussion. One could argue that compared to face-to-face interactions, the threshold for sharing things online is much higher. While some face-to-face interactions are motivated, in many instances there is just conversational space that needs to be filled. It is awkward to have dinner with a friend in silence, or ride in a cab with a colleague without conversing, and so few things will be deemed too boring to talk about (consider how often people talk about the weather). With online WOM, however, the threshold is often higher. Most decisions to post a review or share a news article are not driven by the need to fill conversational space, but by the belief that there is useful or interesting information to be passed along. More practically useful or surprising *New York Times* articles, for example, are more likely to make the most emailed list (Berger and Milkman 2009). Consequently, factors like interest or practical utility may have a greater impact on online transmission.

Another potential difference may be the temporal distance between first experiencing or learning about the product and WOM. People often forward online content (e.g., articles or videos) soon after they find it, but face-to-face interactions often involve discussions about more distal experiences. When a friend asks for a book recommendation, responses depend a lot on memory as people think back to what they read recently. Consequently, how top of mind various experiences are (i.e., accessibility) may play a larger role in face-to-face versus online WOM.

From a practical standpoint, it would also be worth investigating when WOM intentions predict behavior. Many WOM studies use willingness or intentions to talk (e.g., Harrison-Walker 2001), and many companies use measures like Net Promoter Score, which ask consumers about their intentions to recommend. Our results, however, suggest that intentions measures may not always be accurate. Further, such measures may be biased in predictable ways. Intention measure may be driven by lay theories, but in cases where consumers may have less insight into what drives their behavior (e.g., subtle cues in the environment) or rely on theories that may be incorrect (e.g., that people talk more about interesting things) their predictions may be incorrect.

The preceding analysis also suggests that WOM intentions should be reasonably good at predicting online WOM or more motivated face-to-face interactions, because the threshold to talk about something is high. People will only talk if something seems worth talking about, and thus their intentions should be a reasonable proxy. On the other hand, in cases of face-to-face WOM where less motivation exists, intentions may be less accurate because people may overestimate talking about interesting things and underestimate the prevalence of idle chatter about whatever comes to mind.

Future research might also examine how motivation and cues combine to drive WOM. There are some situations where what people talk about may be driven more by self-presentation, information gathering, or building social capital (e.g., Godes et al. 2005; Stephen and Lehmann 2009; Wojnicki and Godes 2009). Accessibility should still play a role in these instances but potentially a more subordinate one. In the absence of motivation, consumers may just talk about whatever comes to mind, but when a particular motivation is active, they will likely select from accessible information based on what best serves the driving motive.

In conclusion, word-of-mouth provides a fertile domain to integrate consumer psychology and marketing science (Winer 1999; Wittink 2004). The emergence of social media and online WOM has provided a wealth of data on what consumers say, share, and do. While analyzing this data correctly requires an appropriate statistical toolkit, it provides the opportunity to address a rich set of behaviorally and managerially relevant questions.

APPENDIX

Model Selection and Goodness of Fit

For the cross-campaign analysis models of overall WOM, we use the following criteria for assessing the goodness of fit: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), likelihood ration test (LRT), a scatter plot of campaign-level predictions versus actual data, and a histogram of predicted number of conversations versus actual data.

We consider a benchmark model containing no predictors to illustrate the relative amount of variation in each layer of unobserved heterogeneity (LL = -7993, AIC = 15,994, BIC = 16023). The three batches of parameters vary across 2,000 agents, 335 campaigns, and 10,968 observations according to independent normal distributions with means zero and standard deviations $\sigma_\alpha = 0.71$, $\sigma_\delta = 0.44$, and $\sigma_\varepsilon = 0.79$, respectively. This suggests that the variation across agents talking propensity and variation across the observation specific error are both greater than the variation across campaigns.

Among models including different product characteristics (Table 3), the model with the best (lowest) BIC and AIC is Model 3.2, which only includes cues and usage per week. In addition, a likelihood ratio test confirms this that adding cues is worthwhile ($\chi^2(1) = 18$, $p < 0.0001$), but adding interesting is not ($\chi^2(1) = 2$, $p = 0.16$). Therefore, Model 3.2 is referred to as the "proposed model" and serves as the basis of comparison for examining the effect of campaign giveaways. In fact, Model 4.2 and Model 3.2 are the same model, but different aspects of the model are presented in the two tables.

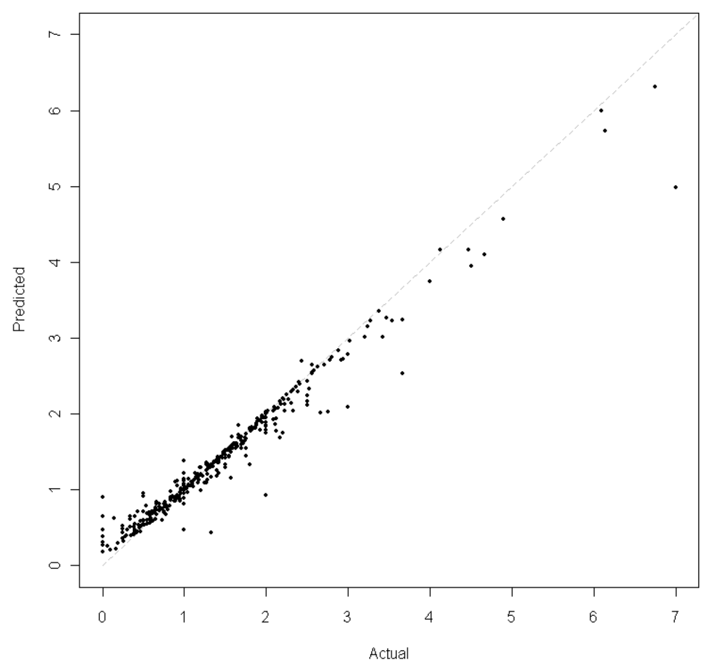
Among models including number of campaign giveaways versus both number and mere presence of those giveaways, the implications for model selection are mixed (Table 4). The model including both number and presence (Model 4.2) is worse than Model 4.1 in terms of BIC and only very slightly better in terms of AIC. The likelihood ratio test reveals that the extra four parameters are hardly worthwhile ($\chi^2(4) = 8.0$, $p = 0.09$). Nevertheless, the objective of this analysis is to test behavioral hypotheses by testing the significance of components of the coefficient vector, β, so we use a model that captures the key aspects of the data and contains covariates allowing us to test these hypotheses. In this case, it is of interest to tease apart the effects of the number of giveaways and the mere presence of each.

The scatter plot in Figure A1 shows that the model does capture the campaign-level average of number of conversations per agent. We look the campaign average because the questions of scientific interest deal with variation in talking across campaigns. We compare the proposed model's predictions of conversations per agent in each campaign with the actual average. The predictions are calculated by taking the campaign-level average of the fitted values based on the individual-level multilevel model. Formally, the Kolmogorov-Smirnov test provides evidence that the proposed model fits the data well ($D = 0.057$, $p = 0.65$). We cannot reject the null hypothesis that the actual and predicted data have come from the same data generating process. The nested models also fit the data well, but not quite as well as the proposed model. The benchmark model without any predictors performs worse ($D = 0.075$, $p = 0.31$), followed by the model with only campaign characteristics, but no product characteristics ($D = 0.063$, $p = 0.53$). The relatively small improvements in fit by adding observed covariates are not surprising given the relatively large amount of variation accounted for by the unobserved parameter heterogeneity across people, products, and observations.

In addition, the histogram in Figure A2 shows that the model captures the variability of the number of conversations each agent reported having in each campaign. Model based predictions are obtained via simulation. We compute the predicted histogram as the average number of counts in each bin across all simulated datasets based on the parameter estimates of the proposed individual-level model.

We also consider other model structures. We choose the Poisson log-normal model instead of the NBD (Poisson-gamma) model to allow all levels of heterogeneity to be normally distributed instead of having two levels normally distributed but one level gamma distributed. Also, we tested a zero-inflated Poisson model, which allowed for two latent segments of observations ("hardcore non-talkers" and "potential talkers" in each particular campaign), but the data likelihood did not significantly improve enough with a this "spike at zero conversations" according to a likelihood ratio test to justify the increase in complexity. This is not surprising given the flexibility of having three layers of parameter heterogeneity and the objective measures of goodness of fit for the proposed model.

Figure A1
Goodness of Fit: Averages of Conversations per Agent for Each Campaign



Note. The Kolmogorov-Smirnov test (D = 0.057, p = 0.65) indicate the data and the model predictions do not come from significantly different generating processes.

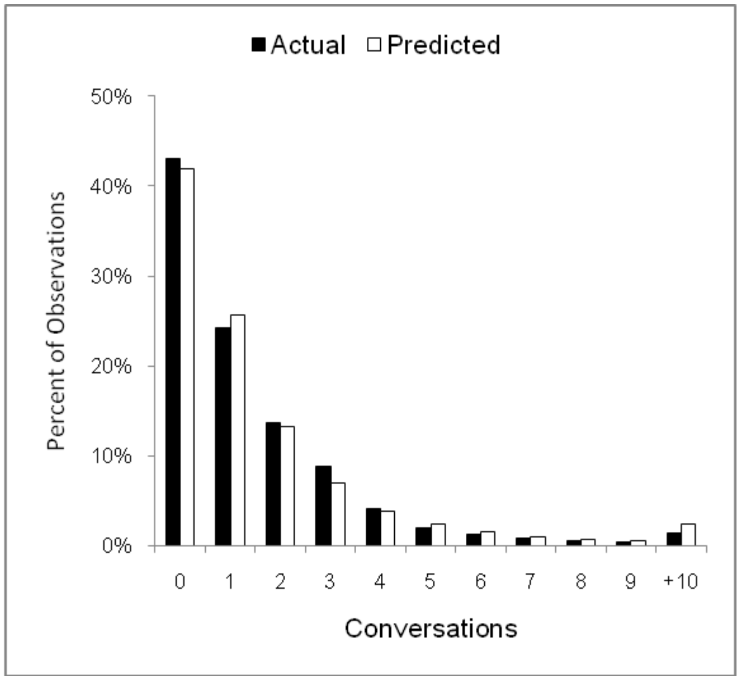


Figure A2
Goodness of Fit: Histogram of Number of Conversations by Agents in Campaigns
Note. A visual inspection of the fit of the histogram of number of conversations each agent had in a campaign shows that the model captures the distribution quite well.

Evidence of Mediation

Our goal is to test the hypothesis that the effect of product usage on WOM is driven by cues. The fact that we have a multilevel generalized linear model means that meditational techniques based on ordinary least squares (OLS) are not sufficient. We follow the recommendation of causal inference work on testing mediation in multilevel models (Krull and Mackinnon 1999; Freedman and Schatzkin 1992). In OLS, the difference between the direct and indirect effect of the predictor is algebraically equivalent to the product of the effect of the predictor on the mediator and the effect of the mediator on the outcome (Baron and Kenny 1986). In a multilevel and non-linear model, this is not the case. By simply just looking at the difference in the change in the direct and indirect effect we can begin to understand the potential mediation. That is the difference in the coefficient of usage in Model 3.1 and in Model 3.2 is 0.020 (= 0.02019 - 0.00058). In other words, the effect of weekly product usage decreases in the presence of cues.

To quantify this difference, we use a test statistic specifically for multilevel models (Freedman and Schatzkin 1992). There is a strong correlation between product usage and cues ($r = 0.43$, $p < 0.0001$). This correlation is used to compute the Freedman-Schatzkin t-stat with N-2 degrees of freedom, where N is the number of observations. For our data, this test allows us to reject the null hypothesis and show evidence of mediation ($t = 6.1$, $p < 0.0001$). On the other hand, the data do not support the reverse of this direction, but only support the hypothesized direction of our mediation.
As an extra check, we use the linear model estimated with OLS on the aggregate campaign-level data to calculate the classic Sobel test statistic, which serves as another

piece of evidence in support of mediation of the effect of product usage on WOM by cues (Sobel z = 3.7, p=0.0001).

Email Message Manipulation

Subject Line: Thinking About [*a Place to Eat / Dinner*]? Think About Boston Market!

Headline: Enjoy the Summertime BBQ Menu [*for dinner*] at Boston Market

Greetings BzzAgent <username>,

Your BzzKit is on its way
We've packed up your BzzKit and shipped it out — if you haven't received it yet, expect it soon. In the meantime, stop by bostonmarket.com to check out all the tasty, affordable and wholesome menu options, whet your appetite and [*see what you could be enjoying right now! / decide what your family or friends want for dinner tonight*!]

Celebrate summer with Boston Market
One of our favorite Boston Market menus is the limited-time-only Summertime BBQ menu. Use your "Be My Guest" card to try it with your family or friends [*tonight for dinner*]. It's good for meals up to $8.99, including the ¼ BBQ Chicken Meal, which comes with two savory, summery sides like baked beans and potato salad. But pick up your summer-inspired [*meal/ dinner*] soon — the Summertime BBQ menu is only available through August 31!

Submit your BzzReports
After such an amazing [*meal / dinner*], you'll probably need a little time to just sit back and savor it for a bit. That's the perfect time to submit a BzzReport to let us know what your family and friends thought about Boston Market and to fill us in on any other Bzz you've created

Notes

[1] Campaigns are generally sequential and most agents are involved in only one campaign at a time.
[2] One could argue that people exaggerate the number of conversations they have to seem hard working, or under report due to laziness. If such biases exist, however, they should occur across campaigns. Other potential selection concerns are addressed in subsection on Potential Limitations.
[3] Campaigns also differ in length, but 80% lasted between 10 and 13 weeks. Campaign length was set with clients before the start of campaigns and was not endogenously extended as campaigns progressed. BzzAgent believes that variation in campaign length should be independent of our variables of interest. We control for campaign length in each model.
[4] High inter-rater reliability and the fact that these measures are averages both reduce measurement error. Any remaining noise should make it harder to find effects, as long as the unobserved heterogeneity of the independent measures is uncorrelated with unobserved biases in our dependent measure across individuals.
[5] To best capture these aspects of the data we use a model that stems from the classic Item Response Theory (IRT) model (Gulliksen 1950; Lord 1980) and standard hierarchical modeling (Gelman and Hill 2007). The traditional IRT framework models individuals responding to various items; we model agents reporting conversations about various product campaigns.
[6] We also consider models on the aggregate campaign-level data where the dependent variable is the average number of conversations per agent per campaign. The aggregate data (a) provide another test of the suggestion that cues mediates the effect of product usage on WOM (see Appendix) and (b) allow us to answer questions regarding moderating effect of timing, where the disaggregate count data are too sparse.
[7] The coefficient values of the coded variables should be interpreted carefully, since these variables are proxies for latent constructs (e.g., interesting) rather than exact measures (e.g. whether a product was given away). The inferences do not change when controlling for price or product involvement, neither of which is significantly associated with WOM. This holds even when price is transformed (log, square root) or when outliers are removed. These variables are also not significantly correlated with any of the other predictors.
[8] Though one could argue that this result is driven by the set of products studied, the fact that the data spans a large number of products (i.e., over 300) from a broad range of product categories (i.e., from movies and cars to household cleanser and food) casts doubt on this possibility. Further, the mean level of interest is similar to other work that has looked at a broad set of cultural items (Berger and Milkman 2009).
[9] Intentions to talk were also correlated with ratings of surprise ($r = .16$, $p < .005$), novelty ($r = .18$, $p < .001$), and originality ($r = .10$, $p = .06$).
[10] We use aggregate campaign-level data for this ancillary analysis because splitting the individual-level conversation data into two time parts left the data too sparse. We estimate the effects using a linear mixed effects model of WOM with random effects to for the two repeated measures from each campaign. Since campaigns vary in length, we performed the analysis on (1) all campaigns and (2) a focused set (125 campaigns) with the modal length (68- 72 days). Results are even stronger when the subset is used.
[11]Effects of campaign characteristics are based on Model 2, but results are robust across specifications.
[12] By using a multilevel modeling approach, we control for the idiosyncratic and unmeasured factors that may affect each agent's talking propensity, each campaign's propensity to be talked about, and the interaction of the two. Thus, any selection story would have to be told above and beyond these controls.
[13] Another aspect of BzzAgent's allocation engine identifies and removes "free loaders," people who sign up for many campaigns to receive free giveaways but have never talked.. This does not differ across campaigns nor should it be correlated with our drivers of interest.
[14] Ancillary analyses cast doubt on the notion that these results could be explained by the manipulation making Boston Market seem more interesting or novel. A separate set of participants ($N = 62$) were given the text of either the control or dinner conditions from the main study and asked to rate how interesting they found Boston Market and how novel they found the campaign. Prior to reading the text, they also completed the measure of how much they associated Boston Market with dinner from the main study. Participants who more strongly associated the chain with dinner found the chain more interesting ($\beta = 0.44$, $SE = 0.14$, $t = 3.16$, $p < .002$), but there were no main effects or interactions due to condition (ts $< .90$, ps $>.39$). This rules out the possibility that the dinner cue somehow made Boston Market more interesting overall, or more interesting among individuals who do not already associate the chain with dinner.

REFERENCES

Agostini, Jean-Michel (1961), "How to Estimate Unduplicated Audiences," *Journal of Advertising Research*, 1(3), 11-14.

Baron, Reuben M. and David A. Kenny (1986), "The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," *Journal of Personality and Social Psychology*, 51(6), 1173-1182.

Berger, Jonah and Gráinne M. Fitzsimons (2008), "Dogs on the Street, Pumas on Your Feet: How Cues in the Environment Influence Product Evaluation and Choice," *Journal of Marketing Research*, 45(1), 1-14.

Berger, Jonah and Katherine Milkman (2009), "Social Transmission and Viral Culture," *Wharton School Working Paper*.

Biyalogorsky, Eyal, Eitan Gerstner, and Barak Libai (2001), "Customer Referral Management: Optimal Reward Programs," *Marketing Science*, (20) 1, 82-95.

Brown, Jacqueline Johnson and Peter H. Reingen (1987), "Social Ties and Word-of-Mouth Referral Behavior," *Journal of Consumer Research*, 14, 350–62.

Carl, Walter J. (2006), "What's All the Buzz About? Everyday Communication and the Relational Basis of Word-of-Mouth and Buzz Marketing Practices," *Management Communication Quarterly,* 19, 601-634.

Carl, Walter J. and Carey M. Noland (2008), "The Conversational Geography of Word-of-Mouth Communication and Marketing Practices, *Communication Quarterly,* 56, 184-207.

Cheema, Amar and Andrew M. Kaikati (2010), "The Effect of Need for Uniqueness on Word-of-mouth," *Journal of Marketing Research*, forthcoming.

Collins, Allan M. and Elizabeth F. Loftus (1975), "A Spreading-Activation Theory of Semantic Processing," *Psychological Review*, 82 (6), 407–428.

Dichter, Ernest (1966), "How Word-of-Mouth Advertising Works," *Harvard Business Review*, 44, 147-166.

Dye, Renee (2000), "The Buzz on Buzz," *Harvard Business Review*, 88, 139-146.

Freedman, Laurence S. and Arthur Schatzkin (1992). Sample size for studying intermediate endpoints within intervention trials of observational studies. *American Journal of Epidemiology*, 136, 1148-1159.

Gelman, Andrew and Jennifer Hill (2007), *Data Analysis Using Regression and Multilevel/Hierarchical Models,* New York: Cambridge University Press.

Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word‐of‐Mouth Communication," *Marketing Science*, 23, 545–60.

Godes, David, Dina Mayzlin, Yubo Chen, Sanjiv Das, Chrysanthos Dellarocas, Barak Libai, Bruce Pfeiffer, Subrata Sen and Mengze Shi (2005) "The Firm's Management of Social Interactions," *Marketing Letters*, 16(3/4), 415-28.

Godes, David (2008), "Blogging at BzzAgent," *Harvard Business School Case 508-102.*

Godes, David and Dina Mayzlin (2009), "Firm-Created Word-of-Mouth Communication: Evidence from a Field Test," *Marketing Science*, 28, 721-739.

Goldenberg, Jacob, Barak Libai and Eitan Muller, (2001), "Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth," *Marketing Letters,* 12(3) 209-21.

Goldenberg, Jacob, Sangman Han, Donald R. Lehmann and Jaewon Hong (2009), “The Role of Hubs in the Adoption Process,” *Journal of Marketing*, 73(March), 1-13
Gulliksen, Harold (1950). *Theory of Mental Tests*. New York: Wiley.
Harrison-Walker, L. Jean (2001), “The Measurement of Word-of-Mouth Communication and an Investigation of Service Quality and Customer Commitment as Potential Antecedents,” *Journal of Service Research*, 4 (August), 60-75.
Hahn, Matthew W. and R. Alexander Bentley (2003), “Drift as a Mechanism for Cultural Change: An Example from Baby Names,” *Proceedings of the Royal Society London B, Biology Letters*, 270, S120-S123.
Heath, Chip, Chris Bell, and Emily Sternberg (2001), “Emotional Selection in Memes: The Case of Urban Legends. *Journal of Personality and Social Psychology, 81*, 1028-1041.
Irwin, Julie R. and Gary H. McClelland (2001), “Misleading Heuristics and Moderated Multiple Regression Models,” *Journal of Marketing Research*, 38 (February), 100–109.
Iyengar, Raghuram, Christophe Van den Bulte, and Thomas W. Valente (2009), “Opinion Leadership and Social Contagion in New Product Diffusion,” working paper.
Kashima, Yoshi (2008), “A social psychology of cultural dynamics: examining how cultures are formed, maintained, and transformed,” *Social and Personality Psychology Compass*, 2, 107-120.
Katz, Elihu and Paul F. Lazarsfeld (1955), *Personal Influence; the Part Played by People in the Flow of Mass Communications*, Glencoe, IL: Free Press.
Keller, Ed and Barak Libai (2009) “A Holistic Approach to the Measurement of WOM," *ESOMAR Worldwide Media Measurement Conference,* Stockholm.
Keller Fay Group (2006), “The Steak is the Sizzle: A Study on Product attributes that Drive Word-of-Mouth Success,” http://www.bzzagent.com/downloads/Keller_Fay_Product_Drivers_Study.pdf
Krull, Jennifer L. and David P. MacKinnon (1999). Multilevel mediation modeling in group based intervention studies. *Evaluation Review*, 33, 418-444.
Leskovec, Jure, Lada A. Adamic, and Bernardo A. Huberman (2007), “The Dynamics of Viral Marketing,” *ACM TWeb* 1(1).
Lord, Frederic. M. (1980). *Applications of Item Response Theory to Practical Testing Problems*. Hillsdale, New Jersey: Erlbaum Associates.
Lynch, John R. Jr. and Thomas K. Srull (1982), “Memory and Attentional Factors in Consumer Choice: Concepts and Research Methods,” *Journal of Consumer Research*, 9 (June), 18-37.
Moe, Wendy W (2009), “How Much Does a Good Product Rating Help a Bad Product? Modeling the Role of Product Quality in the Relationship between Online Consumer Ratings and Sales,” *University of Maryland Working Paper*.
Moldovan, Sarit, Jacob Goldenberg, and Amitava Chattopadhyay (2006), “What Drives Word-of-Mouth? The Roles of Product Originality and Usefulness,” *MSI working papers series*, report number 06-111.
Nedungadi, Prakash (1990), “Recall and Consumer Consideration Sets: Influencing Choice Without Altering Brand Evaluations,” *Journal of Consumer Research*, 17 (December), 263–76.

Niederhoffer, Kate, Rob Mooth, David Wiesenfeld and Jonathon Gordon (2007), "The Origin and Impact of CPG New-Product Buzz: Emerging Trends and Implications," *Journal of Advertising Research*, 47(4), 420-426.

Rosen, Emanuel (2009), *The Anatomy of Buzz Revisited: Real-life lessons in Word-of-Mouth Marketing*, New York: Doubleday.

Rossiter, John R. and Peter J. Danaher, (1998), *Advanced Media Planning*, Norwell, MA: Kluwer Academic Publishers.

Ryu, Gangseog and Lawrence Feick. (2007), "A Penny for Your Thoughts: Referral Reward Programs and Referral Likelihood," *Journal of Marketing*, 71(1), 84-94.

Salganik, Matthew J., Peter S. Dodds, and Duncan J. Watts (2006), "Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market." *Science*, 311, 854-856.

Schaller, Mark and Christian Crandall (2004), *The Psychological Foundations of Culture,* Mahwah, NJ: Lawrence Erlbaum Associates.

Stephen, Andrew and Donald R. Lehmann (2009), "Why Do People Spread Word-of-Mouth? Effects of Recipient and Relationship Characteristics on Transmission Behaviors," *INSEAD Working Paper*.

Van den Bulte, Christophe and Stefan Wuyts (2009), Leveraging Customer Networks, in *The Network Challenge: Strategy, Profit, and Risk in an Interlinked World*, Paul R. Kleindorfer and Yoram (Jerry) Wind, eds., Upper Saddle River, NJ, Wharton School Publishing.

Watts, Duncan J. (2002), "A simple model of global cascades on random networks," *Proceedings of the National Academy of Sciences*, 99, 5766-5771.

Watts, Duncan J. and Peter Sheridon Dodds (2007), "Influentials, Networks, and Public Opinion Formation," *Journal of Consumer Research*, 34, 441-458.

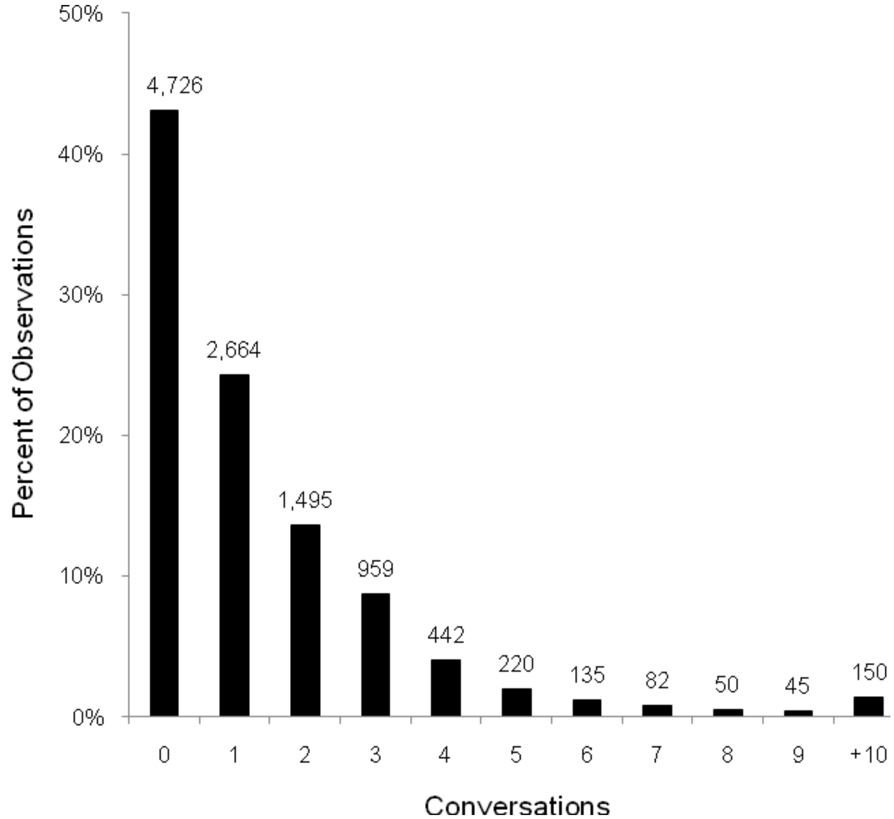
Winer, Russell S. (1999), "Experimentation in the 21st Century: The Importance of External Validity," Journal of the Academy of Marketing Science, 27 (3), 349–58

Wittink, Dick R. (2004) "Journal of Marketing Research: 2 Ps," Journal of Marketing Research, 41 (February), 1–6.

Wojnicki, Andrea C. and Dave Godes (2008), "Word-of-Mouth as Self-Enhancement," *University of Toronto Working Paper*.

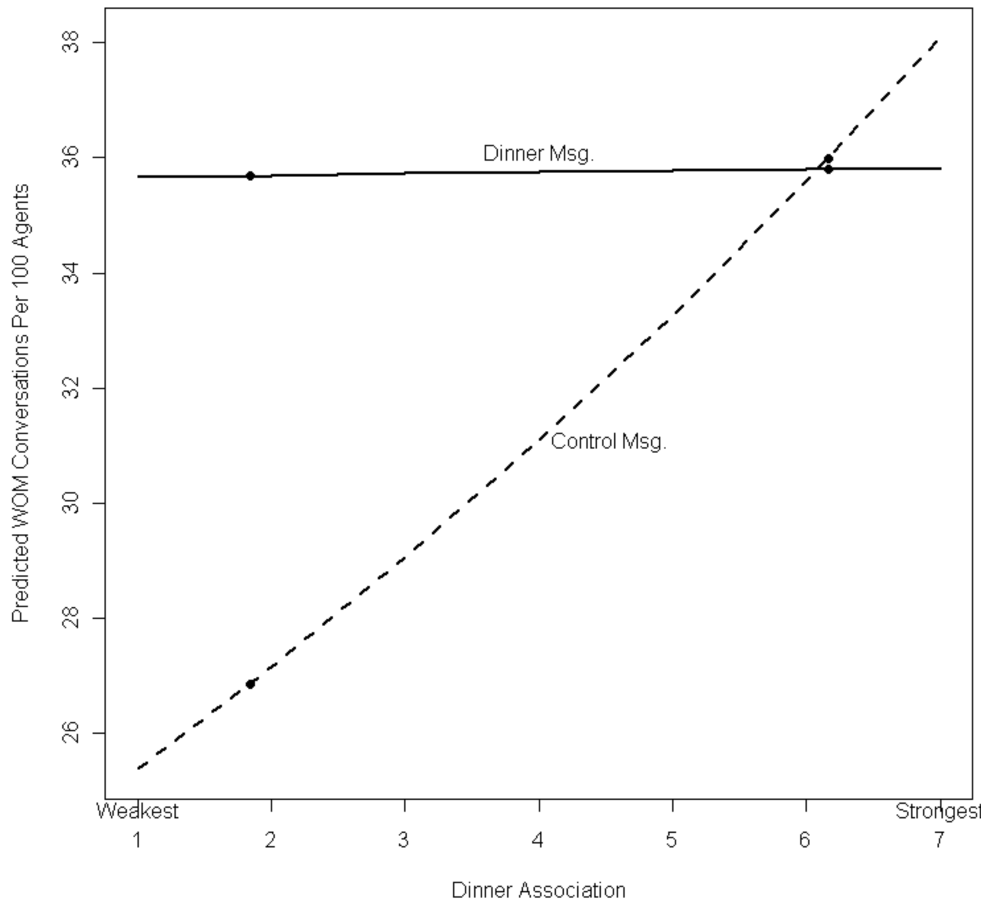
Wu, Fang and Bernardo Huberman (2007), "Novelty and collective attention," *Proceedings of the National Academy of Sciences*, 105(45), 17599-17601.

Figure 1
Cross-Campaign Data: Relative Frequency of Number of Conversations by Agents in a Campaign



Notes. Based on a the sample of all observations from 2,000 agents across 335 campaigns.

Figure 2
Field Experiment: Effect of Dinner Message on WOM is Strongest for People with Weak Dinner Association



Notes. The four points indicate the predicted WOM at one standard deviation below and above the average dinner association for each treatment condition (Dinner Message and Control Message). Hypothesis test for spotlight analysis was conducted following Irwin and McClelland (2001).

Table 1
Summary of Product and Campaign Characteristics and Product Categories

Panel A

Product Charateristics	Units	Means	StdDev	Max	Top1%	Top5%	Top25%	Median	Bottom25%	Min
Usage per Week	Times per week	3.23	4.17	23	18	13	5	2	0	0
Cues	1 to 5 Likert	2.94	1.19	5	5	5	4	3	2	1
Interesting	1 to 5 Likert	1.93	0.73	5	4	3	2	2	1	1
Price	$USD	640	5976	75625	12385	172	20	10	4	0

Panel B

Campaign Giveaways	Units	Means	StdDev	Max	Top1%	Top5%	Top25%	% of Campaigns
Free Products	Count	0.91	1.27	10	6	3	1	57%
Samples	Count	1.48	5.28	60	20	10	0	16%
Extras	Count	2.46	5.6	60	19	11	3	47%
Coupons and Rebates	Count	3.24	4.59	20	20	11	6	53%

Panel C

Product Categories Represented in Data

Category	Proportion
Packaged Food	20%
Books	18%
Household Products	13%
Personal Care	10%
Entertainment/Games	7%
Software/Technology	6%
Pharma/Medical	4%
Retail	4%
Beers/Wines/Spirits	4%
Travel & Tourism	3%
Financial Services	2%
Restaurant	2%
Auto Care	1%
Clothing/Fashion	1%
Other	4%

Table 2
Correlation Matrix for Product Characteristics and Campaign Giveaways

	Usage	Cues	Interesting	Presence of Product	Number of Products	Presence of Sample	Numember of Samples	Presence of Coupon or Rebate	Number of Coupon and Rebates	Presence of Extras	Number of Extras
Usage	1.00										
Cues	0.55	1.00									
Interesting	-0.02	-0.22	1.00								
Presence of Product	0.10	0.08	0.02	1.00							
Number of Products	0.13	0.13	0.03	0.62	1.00						
Presence of Sample	0.17	0.18	-0.17	0.07	0.01	1.00					
Numember of Samples	0.14	0.21	-0.15	0.01	0.00	0.64	1.00				
Presence of Coupon or Rebate	0.13	0.43	-0.14	-0.17	-0.08	-0.01	0.01	1.00			
Number of Coupon and Rebates	0.13	0.37	-0.17	-0.05	-0.02	0.12	0.13	0.66	1.00		
Presence of Extras	0.10	0.00	0.06	-0.11	-0.11	-0.07	-0.12	0.05	0.09	1.00	
Number of Extras	0.00	-0.04	0.01	-0.01	-0.05	-0.03	-0.07	-0.05	-0.01	0.47	1.00

Notes: Shaded values indicate absolute value of correlation larger than 0.30 *and* a difference from 0 at the 5% significance level.

Table 3
Cross-Campaign Analysis: Product Characteristics

Variable	*Model 3.1* Estimate	t	*Model 3.2* Estimate	t	*Model 3.3* Estimate	t
Product Characterstics						
β: Product Usage Per Week	**0.020**	**3.32** *	0.001	0.08	0.002	0.34
β: Cues			**0.147**	**5.45** *	**0.135**	**4.90** *
β: Interesting					-0.068	-1.90
Campaign Giveaways	Yes		Yes		Yes	
Unobserved Heterogeneity	Yes		Yes		Yes	
Goodness of Fit						
LL	-7961		-7952		-7951	
AIC	15,952		15,936		15,936	
BIC	16,062		16,053		16,060	
Num. of Observations	10,968		10,968		10,968	

Notes. *Campaign Giveaways* indicates a set of variables for both the number of each item and an indicator to control for each item's mere presence (see Table 4). In addition, the models include a control for campaign length (weeks), whether a product could be given away, and an intercept. Estimates that are statistically significant ($p < 0.05$) are bold and starred. AIC is Akaike Information Criterion, and BIC is Bayesian Information Criterion. The hierarchical models are not estimated using fully Bayesian inference, rather by quasi-likelihood estimation technique involving a Laplace approximation. This procedure is standard in statistical packages like R and SAS for multilevel mixed models. The t-statistics are computed based on asymptotic standard errors. Equivalently, we could display confidence intervals (e.g., coefficient plus/minus approximately two standard errors) to reflect the variability in the estimates and examine the intervals' coverage of zero.

Table 4
Cross-Campaign Analysis: Campaign Giveaways and Reach and Frequency Models

Variable	*Model 4.1* Estimate	t		*Model 4.2* Estimate	t		*Reach* Estimate	t		*Frequency* Estimate	t	
β: Intercept	**-0.642**	**-11.58**		**-0.655**	**-9.03**		**-0.554**	-10.99		**-0.714**	**-8.33**	
Campaign Giveaways												
β: Presence Product				**0.285**	**3.55**	*	**0.579**	**10.30**	*	**0.242**	**2.58**	*
β: Presence Sample				-0.018	-0.22		-0.006	-0.11		0.008	0.08	
β: Presence Extras				0.035	0.62		0.077	1.93		0.025	0.40	
β: Presence Coupon or Rebate				-0.007	-0.10		**0.153**	**3.18**	*	-0.027	-0.34	
β: Num. Products	**0.043**	**2.10**	*	0.005	0.20		0.001	0.09		0.015	0.57	
β: Num. Samples	0.008	1.80		**0.011**	**1.99**	*	**0.018**	**4.79**	*	0.010	1.55	
β: Num. Extras	**0.011**	**2.62**	*	**0.009**	**2.01**	*	0.000	0.06		**0.010**	**2.00**	*
β: Num. Coupon or Rebates	0.007	1.30		0.007	1.05		**0.016**	**3.17**	*	-0.002	-0.27	
Product Characterstics												
β: Product Usage Per Week	0.002	0.29		0.001	0.08		-0.001	-0.29		0.001	0.07	
β: Cues	**0.143**	**5.44**	*	**0.147**	**5.45**	*	**0.222**	**11.69**	*	**0.143**	**4.63**	*
Unobserved Heterogeneity												
σα: Agents	0.71			0.71			0.46			0.83		
σδ: Campaigns	0.39			0.38			0.24			0.41		
σε: Observation Error	0.79			0.79			0.31			0.82		
Goodness of Fit												
LL	-7956			-7952			-6265			-5005		
AIC	15,937			15,936			12562			10042		
BIC	16,024			16,053			12678			10150		
Num. of Observations	10,968			10,968			10968			6242		

Notes. Estimates that are statistically significant ($p < 0.05$) are bold and starred. The models include a control for campaign length (weeks) and whether a product could be given away.