MARKETING SCIENCE
Vol. 28, No. 4, July–August 2009, pp. 721–739
ISSN 0732-2399 | EISSN 1526-548X | 09 | 2804 | 0721

DOI 10.1287/mksc.1080.0444

Firm-Created Word-of-Mouth Communication: Evidence from a Field Test

David Godes
Graduate School of Business Administration, Harvard University, Boston, Massachusetts 02163, dgodes@hbs.edu

Dina Mayzlin
School of Management, Yale University, New Haven, Connecticut 06520, dina.mayzlin@yale.edu

In this paper, we investigate the effectiveness of a firm's proactive management of customer-to-customer communication. We are particularly interested in understanding how, if at all, the firm should go about effecting meaningful word-of-mouth (WOM) communications. To tackle this problem, we collect data from two sources: (1) we implement a large-scale field test in which a national firm created word of mouth through two populations: customers and noncustomers, and (2) we collect data from an online experiment. We break our theoretical problem into two subproblems. First, we ask: "What kind of WOM drives sales?" Motivated by previous research, we hypothesize that for a product with a low initial awareness level, WOM that is most effective at driving sales is created by less loyal (not highly loyal) customers and occurs between acquaintances (not friends). We find support for this in the field test as well as in an experimental setting. Hence, we demonstrate the potential usefulness of exogenously created WOM: conversations are created where none would naturally have occured otherwise. Then, we ask: "Which agents are most effective at creating this kind of WOM?" In particular, we are interested in evaluating the effectiveness of the commonly used opinion leader designation. We find that although opinion leadership is useful in identifying potentially effective spreaders of WOM among very loyal customers, it is less useful for the sample of less loyal customers.

Key words: word of mouth; promotion; advertising
History: Received: July 21, 2004; accepted: February 21, 2008; processed by Eitan Muller. Published online in *Articles in Advance* January 7, 2009.

1. Introduction

In September 2005, NBC launched the second season of its reality show about weight loss, *The Biggest Loser*. In preparation for the new season, NBC ran ads in early August asking viewers to fill out a survey at a website. Out of all the applicants, 1,000 "biggest" fans were chosen to throw parties during an advanced screening of the show's premiere. The hope was that this, along with the resulting word of mouth (WOM), would generate interest in the show (O'Malley 2005). In 2001, Lee Dungarees wanted to improve its image with teen boys. Their agency identified 200,000 "influentials" from online communities devoted to video games. The firm then e-mailed each a series of short films from unknown characters who turned out to be protagonists in a video game commissioned by the firm. On average, these films were forwarded to about six people each. To play the game, however, one had to go to a retail store and get a code from a pair of Lee jeans (Khermouch and Green 2001). In March of 2006, WD-40 hired Proctor & Gamble (P&G) to promote its new product extension, the "No-Mess" pen. The product was promoted through P&G's Vocalpoint, a panel of influential moms who were preselected via a survey based on their ability to be "connectors" (Neff 2006). Hasbro in 2001 launched a new handheld video game called POX. To do so, they ran surveys in Chicago area elementary schools to find the "coolest" kids in each school. Once 1,600 kids were chosen, they were each armed with a backpack filled with samples of the game to be handed out to their friends (Godes and Ofek 2004).

There are several common threads among these examples. First, the firms in these cases tried to "engineer" WOM among their customers. That is, rather than hoping that satisfied customers would tell people about their products, these firms took actions to increase the number of conversations that were taking place. Hence, we can think of firm-created WOM as a hybrid between traditional advertising and consumer word of mouth in that the former is firm initiated and firm implemented, whereas the latter is customer initiated and customer implemented. WOM marketing, on the other hand, may be characterized as being firm initiated but customer implemented.

Second, they each attempted to identify who the "key influencers" would be in their respective situations. NBC used self-reporting, Lee Dungarees used observational methods, Hasbro used a combination of sociometry and self-reporting, and WD-40 found a fit between its product and the Vocalpoint panel. For each firm, the implementation of their WOM campaign played a primary role in their marketing effort during the respective time period. One notable difference is in the approaches undertaken by the marketers of the two mature products, NBC and Lee Dungarees. Whereas NBC recruited the most loyal users for its campaign, Lee Dungarees instead focused its efforts on influentials, regardless of their existing relationship to the product.

The past several years have witnessed a marked increase in attention paid to "buzz" in the popular and managerial press. In February 2007, a search for "word-of-mouth marketing" in the title yielded 16 different books at Amazon.com. Managers' motivation for looking toward interpersonal communication as a potential new tool grows out of a sense that traditional media advertising is declining in effectiveness, particularly with respect to younger demographic groups (Keller and Berry 2003). However, for all of the importance that managers are apparently placing on the creation of these WOM strategies, there has been little academic research looking at WOM *from the firm's perspective*. In this paper, we address this issue by first investigating whether a firm can orchestrate a WOM campaign that drives sales. This is a materially different question from that of whether naturally occurring WOM may drive sales. Next, we examine what type of WOM the firm should create to impact sales. In particular, should a firm adopt NBC's strategy of focusing on its loyal customers to spread WOM or should it instead try to adopt Lee Dungarees' strategy of spreading the message through people who may not have an existing strong relationship to the product? The former strategy is often advocated in the business and popular press.[1] Finally, we turn to the firm's targeting problem in its design of a WOM marketing campaign. What are the characteristics of the disseminators who are associated with higher amounts of impactful WOM? Do these characteristics differ between loyal and less loyal consumers? To what extent are the existing scales—those designed to predict naturally occurring WOM—effective at measuring the propensity to spread firm-created WOM?

[1] "When customers are truly thrilled about their experience with your product or service, they become outspoken 'evangelists' for your company. Savvy marketing professionals are discovering that this group of satisfied believers can be converted into a potent marketing tool to grow their customer universe" (McConnell and Huba 2003, inside flap).

To answer these questions, we collect two types of data. First, with the cooperation of two separate firms, we collect field data as part of a WOM marketing campaign. In this campaign, two types of people were engaged in the process of information dissemination: (a) a set who had demonstrated behavioral loyalty through their usage of the firm's product, and (b) a panel who had no loyalty to the firm. In addition, we run an online experiment. The experiment allows us to control for variables that are difficult to control in the field and to explore the mechanism behind the effects.

We provide three sets of results. Using field data, we empirically demonstrate for the first time, to our knowledge, that the firm can create WOM that drives sales. This is an important result and is distinct from previous work that has demonstrated that naturally occurring WOM can drive important outcomes (Chevalier and Mayzlin 2006, Manchanda et al. 2008, Godes and Mayzlin 2004, Van den Bulte and Lilien 2003, Foster and Rosenzweig 1995). This is the first study to our knowledge to demonstrate that discussions created by the firm's actions rather than simply product experiences can have such an effect. From a managerial perspective, this result gives credence to the evolving notion that not only is WOM important but it is actually something that is under the firm's control (Biyalogorsky et al. 2001, Mayzlin 2006, Godes et al. 2005, Keller and Lehmann 2006).

Second, we demonstrate that it is not necessarily the highly loyal customers who generate the important incremental WOM, as one might expect. On the contrary, we argue—and present evidence—for the idea that *it may be more impactful for the firm to target less loyal customers* to participate in a WOM campaign. The result is somewhat surprising ex ante but it actually follows directly from commonly accepted ideas about social networks. Specifically, for a product with an initially low awareness level (such as the one studied here), a WOM campaign is primarily beneficial to the extent that it results in the spread of information (as opposed to influence or persuasion). Very loyal customers are likely to live in social networks in which either (a) others are also loyal to the firm or (b) others are aware of but not interested in the firm's products. Both of these imply that WOM from a less loyal customer is likely to have a bigger impact.

Finally, having demonstrated that the firm should look for less loyal customers to spread WOM, we engage in an exploration of how the firm might find those less loyal customers most likely to engage in WOM. In this regard, we demonstrate that while "opinion leadership" is associated with a higher propensity to spread WOM among loyal consumers, the same is not true for less loyal customers.

The rest of the paper proceeds as follows. The following section presents the theoretical background to our hypotheses. In §3, we outline the setup of the field test. In §4, we present results from the field data as well as a follow-up online experiment on the impact of firm-created WOM on sales. In §5, we study who creates impactful WOM. The paper concludes with a discussion of the results and suggestions for future research in this area.

2. Theoretical Development

Beginning with Katz and Lazarsfeld (1955) nearly half a century ago, the impact of WOM on consumers' actions, preferences, and choices has been of great academic interest. Researchers such as Coleman et al. (1966), Arndt (1967), and Engel et al. (1969) have corroborated the primacy of WOM as a key driver of firm sales. These findings have also informed models of product diffusion on aggregate data (see Van den Bulte and Joshi 2007 for a recent example). Other researchers have inferred the impact of WOM from the geographical evolution of sales data: Foster and Rosenzweig (1995), Garber et al. (2004), Bell and Song (2004), and Manchanda et al. (2008). Godes and Mayzlin (2004) demonstrate a positive relationship between online WOM—in particular, its "dispersion" across communities—and ratings for television shows. Van den Bulte and Lilien (2001) question the conclusion reached by Coleman et al. (1966), and the same authors later determined that a more sophisticated decomposition of the physicians' adoption decision did, in fact, yield evidence for the role of interpersonal influence (Van den Bulte and Lilien 2003).[2]

We distinguish between "endogenous WOM" and "exogenous WOM." The literature has focused primarily on the former, which is characterized by conversations that occur naturally among consumers as a function of their experiences with the product. In contrast, the latter refers to WOM created as the result of the firm's actions. The literature has shown the important relationship between endogenous WOM and sales, but this does not necessarily imply that either creating a substantial amount of exogenous WOM is possible for the firm or that such exogenously created WOM would have the same beneficial impact on the product's sales as previous research has demonstrated with respect to endogenous WOM. That is, can firms get people to talk about their products in such a way that it impacts sales? Moreover, if so, how?

[2] Whereas most studies have been interpreted as suggestimg that positive WOM may lead to an increase in sales, it is also possible that market potential remains the same but that WOM instead accelerates the product's adoption up to the potential. We thank an anonymous reviewer for pointing this out.

The answers are not necessarily obvious. On one hand, there is a question about whether the firm should bother building exogenous WOM. Is a WOM marketing program an effective way to attract customers? This issue is addressed by Biyalogorsky et al. (2001), who investigate the optimality of customer referral programs, comparing them to another method of attracting customers: cutting prices. Biyalogorsky et al. (2001) show that the firm should offer rewards for customer referrals only if people are somewhat demanding but not too demanding. Assuming that an effective WOM marketing program is desired, one needs to ask whether it is feasible given the inferences a recipient of WOM information may draw. The persuasion knowledge model (Friestad and Wright 1994) suggests that when confronted with a persuasion attempt, one may process the message in such a way that a "change in meaning" may occur. This model has been applied to the WOM domain by Verlegh et al. (2004) who show that when consumers perceive ulterior motives, the effectiveness of the sender's WOM communication may be decreased. This work focused on individual- and message-level inferences, but it is also possible that inferences can be drawn with respect to firm strategies. This issue is addressed by Mayzlin (2006) who shows that the firm's creation of anonymous online WOM may be a profitable equilibrium strategy even when consumers are aware of the possibility that the firm is creating it. On the other hand, when the costs of creating anonymous WOM are very low, consumers discount received messages, which in turn implies that the program does not work.

We add to this literature on the feasibility, attractiveness, and optimal design of WOM marketing programs by decomposing the problem into two separate subproblems. We begin by developing a theoretical foundation for why some kinds of exogenous WOM are more or less likely to lead to higher sales for a firm. We then consider the question of identifying those disseminators who are most likely to create impactful WOM.

2.1. What Kind of Exogenous WOM Matters?

As with other media, a WOM campaign might impact outcomes by affecting (a) awareness or (b) preference. That is, exposure to a WOM episode might make consumers aware of a product they had not been aware of before, or it might persuade them by changing the expected utility they had assigned to that product. In fact, there may be an inherent tension between achieving these two objectives: those disseminators who may be most persuasive may not be the ones who will help the firm achieve maximal awareness.

The literature on influence has strong predictions on how decision makers are affected by their peers.

For example, Reingen et al. (1984) show that consumers' brand choices within a social group are often congruent. There is also an extensive literature documenting that the similarity between sender and recipient may increase the persuasiveness of the communication (Cialdini and Sagarin 2005, Kruglanski and Mayseless 1990, Mazen and Leventhal 1972). Similarity may be especially important when new attitudes and beliefs are formed—such as for a new product (Kardes 2002)—and for certain types of products such as public luxuries (Bearden and Etzel 1982). Thus, we would expect a communication with a friend or a relative to be more *persuasive* than a conversation with an acquaintance or a stranger. The disseminator's expertise with the product has also been found to increase the influence of her advice (Petty et al. 2005). This would seem to indicate that a loyal disseminator—one who is more familiar with the product—is more likely to be persuasive than a less loyal disseminator.

However, the characteristics of WOM that are typically associated with higher persuasiveness may, on the other hand, be associated ultimately with less breadth of awareness of the message. Granovetter (1973) showed that it is essential to distinguish between "strong ties" and "weak ties" in understanding the flow of interpersonal information. An important argument in this work is that weak ties form the bridges between otherwise isolated strong tie networks. Because those in the same social networks are likely to have similar information, it is often information communicated via a weak tie that results in a greater increase in the number of new people who are informed. Goldenberg et al. (2001) use cellular automata to investigate the relative macrolevel impact of strong and weak ties and find that the latter may have a bigger impact even though the former are activated more frequently. A fundamental implication of this research is that information transmitted between acquaintances or strangers should ultimately reach more people—i.e., lead to higher awareness—than if it had been transmitted between friends or relatives.

Although the effectiveness of WOM may depend on the strength of the tie across which a message is communicated, this is not easily managed by the firm within the context of a WOM marketing campaign. However, the same critical dimension—the extent to which WOM reaches previously uninformed customers—may also be related to more easily identifiable customer characteristics as well. We investigate here the role of customer loyalty. This is an attractive criterion because it is relatively easy for the firm to select customers for inclusion in a WOM campaign based on loyalty. However, the definition of loyalty is not without disagreement. One might characterize the choice as being between a "behavioral" measure or an "attitudinal" measure. The former is typically characterized by repeat purchase behavior and the latter "includes a degree of dispositional commitment" to the brand (Chaudhuri and Holbrook 2001). Although one is not necessarily better than the other, it is clear that the measures are quite distinct (Jacoby and Kyner 1973). For the purpose of designing a WOM marketing campaign, we argue that behavioral measures may be more practical because most firms have access to some measure of behavioral loyalty. Capturing attitudinal loyalty for all but a sample of customers is likely to be a difficult undertaking. Thus, the approach we take in our core empirical analysis is to adopt observed behavior as a measure of loyalty. In our experimental analysis, we add an attitudinal component to our measure to check the robustness of our results.

Following past research, we expect loyal customers to be more satisfied with the product than average (Anderson and Sullivan 1993) and, hence, to have created more WOM than average (Bowman and Narayandas 2001, Anderson 1998, Bolton and Drew 1992, Reichheld and Sasser 1990, Swan and Oliver 1989, Holmes and Lett 1977). As a result, we expect that those with ties, weak or strong, with loyal customers are more likely to already have been informed about the firm and its products *before* the beginning of the WOM campaign. Hence, the *incremental* WOM created by a less loyal customer would result in greater awareness compared to that created by a loyal customer because of the lower levels of endogenous WOM that were created by the less loyal customers.

In summary, we expect the persuasiveness of a message to be highest when sent by a loyal customer to friends and relatives. On the other hand, we expect the ex post breadth of awareness to be higher when the message is sent by a less loyal customer to acquaintances and perhaps strangers. Whether the firm should maximize awareness or persuasiveness is a function of the status quo prior to the campaign. If the product is well known, then the firm should probably concern itself with persuading consumers of the product's value. On the other hand, if the price of trial is relatively low and if there is not a lot of existing awareness, then the firm might concentrate primarily on the spread of information. Here, we assume that the latter better matches our field study context. As we demonstrate in §3, awareness is relatively low for the product under study. Hence, we expect that a WOM campaign would have a bigger marginal impact by creating conversations where none ordinarily would take place rather than amplifying conversations that are already naturally occurring. More formally, we posit the following two hypotheses:

Within the context of an exogenous WOM campaign for a product with low initial awareness levels, Hypothesis 1 (H1). *The sales impact of incremental WOM from a less loyal customer is higher than that from a loyal customer.*

Hypothesis 2 (H2). *The sales impact of incremental WOM to an acquaintance is higher than that to either a friend or a relative.*

Note that by placing the hypotheses within the context of an exogenous WOM campaign, we are assuming that most (if not all) of the word of mouth is positive. If the comments were negative (as may be the case in naturally occurring conversations), H1 and H2 may no longer hold. First, negative news from a loyal customer would presumably be new information to his or her social circle, which may mitigate some of the awareness differences between the social circles of the loyal and the less loyal customers. Second, a negative recommendation coming from a previously loyal customer may be especially persuasive.[3]

We emphasize that the main contribution of the current paper lies in H1. Our test of H2 represents an important field test of the application of the influential results reported by Granovetter (1973). It is useful to relate H1 to the customer relationship management literature. A traditional calculation of customer lifetime value considers direct purchases only (see Gupta et al. 2006b) and would imply that the loyal customers are the firm's most valuable asset. However, as has been noted in the recent literature (Hogan et al. 2003, Rust and Chung 2006), the value of a lost customer does not just include the revenue generated directly by the customer but also the lost value of the social interactions associated with the customer. Gupta et al. (2006a) find sizable network effects in an online auction site. Here, we suggest that the network effects associated with WOM may be especially large for less loyal customers, which would have important implications on optimal allocation of resources to customer retention. Specifically, it may suggest that less loyal customers are more valuable than current models give them credit for.

2.2. Who Creates WOM That Matters?

The examples offered in §1 suggest that the implementation of a WOM campaign requires that the firm identify effective disseminators of information. Here, we focus on "opinion leadership," a designation that is commonly discussed in the context of word of mouth in marketing (see Katz and Lazarsfeld 1955, King and Summers 1970, Jacoby and Hoyer 1981, Bloch and Richins 1983, Rogers 1993). King and Summers (1970) offer a scale for this purpose. Although this has proven to be a reliable scale in general, little research has investigated potential moderators of the opinion leader-WOM relationship. We investigate here the moderating role of loyalty. Although we would expect a *loyal* opinion leader to create WOM, it is less clear what the WOM behavior of a less loyal opinion leader would be. If we conceptualize an opinion leader as Bayesian with a distribution over the firm's value, she may not be "loyal" because (a) her prior is low or (b) the distribution is too diffuse. Clearly, in the former case, being an opinion leader would not increase the likelihood of positive WOM. In fact, it may increase the likelihood of negative WOM.

With respect to (b), the customer may be uncertain about the product because of lack of experience with it. As noted by Rogers (1993, p. 296),

> If an opinion leader becomes too innovative or adopts a new idea too quickly, followers may begin to doubt the opinion leader's judgement. One role of the opinion leader in a social system is to help reduce the uncertainty about an innovation for his or her followers. To fulfill this role, the opinion leader should demonstrate prudent judgement in decisions about adopting new ideas.

Opinion leaders risk losing their status when they become "too innovative," recommending products that those in their social circle are not ready to adopt. We hypothesize that the same mechanism exists with respect to product familiarity. As a result, opinion leadership should be a less useful predictor of WOM in a low loyalty context as compared with the high loyalty context. Specifically, we expect an interaction between opinion leadership and loyalty in a model of WOM volume:

Hypothesis 3 (H3). *Whereas opinion leadership is associated with the creation of more WOM for loyal customers, this is less true for less loyal customers.*

3. Data Collection

To test the hypotheses above, we collected two types of data: (1) we designed and implemented a field test, and (2) as a follow-up to the field test, we conducted an online experiment.

3.1. Field Test Setup

The field test included two organizations: an agency (BzzAgent) and a restaurant chain (Rock Bottom Brewery). At the time of the study, Rock Bottom Brewery did business in 15 markets across the United States. The firm's gross sales in the 12 months leading up to the program were over $100 million.[4] The firm's product line is split into five categories, with 21% in category A. Crucial to our test is the fact that Rock Bottom maintains a loyalty program centered around category A. Several thousand customers hold a card

[3] We thank an anonymous reviewer for pointing this out.

[4] At the request of Rock Bottom, we do not reveal detailed or disaggregate financial information.

that they present at the time of purchase. After a specified number of purchases, they are rewarded with prizes including free products, coupons, and other promotions.

BzzAgent is a marketing agency engaged in the business of creating WOM communication for its clients. To do so, BzzAgent maintains a panel of "agents." In a standard project, the agency agrees to lease a specified number of its agents to the client. As part of this agreement, BzzAgent trains the agents and manages the process in which the agents create WOM for the client. Prior to this research project, BzzAgent had only run campaigns using its panel of agents and had never worked with its clients' own customers.

The field test, which lasted 13 weeks, involved a comparison of the WOM created by these two populations: the members of the firm's loyalty program on one hand, and the agency's panel on the other. We refer to the former as "customers" and the latter as "noncustomers" because they had little to no information about the retail chain before the study. Subjects were invited to participate in the field test via an e-mail from either BzzAgent (for noncustomers) or Rock Bottom (for customers). The e-mail explained what the campaign was about and noted that their participation and performance would qualify them for potential prizes. The objective was to recruit a total of 1,000 subjects. The process ultimately yielded 381 customers and 692 noncustomers who agreed to participate in the program. Among customers, 99% answered "yes" when asked whether they "liked" the firm, 0.5% answered "no," and 0.5% reported that they were indifferent. All of the BzzAgents were invited to participate in the campaign and the customers were invited on a rolling basis such that the most loyal customers (those who were the heaviest users of firm's category A product) were invited first, followed by those who were somewhat less loyal, etc. E-mail invitations continued in this fashion until a sufficient number of customers had registered. To our knowledge, no other major advertising effort had taken place during the duration of the field test.

Among the 692 noncustomers, 213 had previously participated in campaigns for the agency's clients. Of these, 47% had worked on one campaign, 29% on two, 17% on three, and 7% on four. Of noncustomers, 86% had never heard of the chain prior to the project. By design, the sample populations were mutually exclusive; none of the noncustomers were members of the firm's loyalty program. Once they agreed to participate in the campaign, subjects were directed to a website to fill out an extensive survey. The instrument captured demographic information such as category-level opinion leadership as well as demographic data that we expected would be useful in building an individual-level model of WOM creation. There

Table 1 **Summary Statistics**

WOM variables					
Variable	*N*	Mean	Std. dev.	Min	Max
Customer to relative	180	0.13	0.40	0	2
Customer to friend	180	1.31	1.87	0	10
Customer to acquaintance	180	0.51	0.95	0	5
Customer to stranger	180	0.51	0.92	0	5
Customer to other	180	0.51	1.08	0	6
Noncustomer to relative	180	0.20	0.49	0	3
Noncustomer to friend	180	0.95	1.61	0	10
Noncustomer to acquaintance	180	0.43	0.82	0	6
Noncustomer to stranger	180	0.52	0.99	0	6
Noncustomer to other	180	0.53	1.03	0	5

appear to be some differences between the customer and noncustomer sample based on the available demographic data (see Table 1 in the Technical Appendix).[5] In particular, customers on average are older, more likely to work full time, less likely to be students, and eat out more often than noncustomers. Notably, customers and noncustomers do not differ significantly in terms of opinion leadership.

After filling out the online survey, each participant received a package of information about Rock Bottom and its products as well as specific suggestions for creating WOM for the firm. This package also contained specific details on how the campaign would be run and how the agents were to participate. The WOM creation process officially began in April 2003 and ran through June 2003. Once it began, the agents were asked to report their WOM creation activity. They were directed to a website through which they were to report in detail each time they engaged in a WOM episode.[6] Importantly, each agent provided information on his or her relationship with a recipient: whether he or she was a friend, relative, acquaintance, stranger, or some other relationship. Note that the participants often reported the transmission of information to *several* people in a single report. That is, a single report often represented more than a single new person being informed. Each WOM report was graded on its potential to create meaningful WOM. The grading was handled by the agency's staff as part of their normal contract obligations. Participants had an incentive to create meaningful WOM because the higher their scores, the more prizes they were able to win. Nonetheless, these incentives were extremely low powered: the average prize was valued

[5] The Technical Appendix can be found at http://mktsci.pubs.informs.org.

[6] For example, an agent for another BzzAgent campaign, Al Fresco chicken sausage, reported that she "wrote to a local priest known for his interest in Italian food, suggesting a recipe for Tuscan white-bean soup that included Al Fresco sausage. The priest wrote back to say he'd give it a try" (Walker 2004).

at around \$15. Moreover, the agency reports that most of the points earned by participants are never, in fact, redeemed. That the agents are willing to devote time to an activity with little economic reward would seem to suggest a certain level of intrinsic motivation. This might stem, for example, from altruism or perhaps the desire to be "in the know."

Note that the self-reported nature of the WOM episodes may give rise to some exaggeration. However, the bias should be the same for both customers and noncustomers. Moreover, if it were the case that actual WOM was significantly lower than that reported, we would not expect to find any impact of reported WOM on sales. Hence, whether such reports are a useful measure is ultimately an empirical question.

In summary, our field test ran in 15 markets for 13 weeks. We have data on the amount of WOM created by each agent over those weeks, on the relationship between the agent and the recipient, and on the individual characteristics of each agent. Moreover, we have sales data at the market level for each week of the campaign and for year-earlier periods.

4. The Effect of Exogenous WOM on Sales

In this section, we ask whether the firm can create exogenous WOM that drives sales, and if so, how? Our core analysis is performed on data from the field test. We also present data from a follow-up online study that allows us to control some factors that were difficult to control adequately in the field.

4.1. Field Test

Because H1 and H2 relate to firm sales, we test them with an aggregate market-level model. The main model we estimate is as follows:

$$S_{it}^{A} = \sum_{j\in C,\,N}\left[\sum_{r\in R}\omega_j^r \cdot WOM_{ij(t-1)}^{r}\right] + \sum_{i=2}^{15}\mu_i + \sum_{t=2}^{12}\tau_t + \varepsilon_{it}, \quad (1)$$

where S_{it}^{A} represents sales of category A in market i in week t. Note that we focus here on the impact of WOM on category A sales because this is both where the loyalty program is focused and where the campaign itself was targeted. Our WOM data are captured in $WOM_{ij(t-1)}^{r}$, where $r \in R = \{friend, relative, acquaintance, stranger, other\}$ is the set of possible relationships between the sender and receiver of WOM information. We define $WOM_{ij(t-1)}^{r}$ as the total *number of reports* filed in week $t-1$ in market i that reflected WOM from someone in condition j (i.e., customer or noncustomer) to a person *or people* with whom they have a relationship that can be characterized by r. We do not know exactly how many people this WOM episode impacted; we only know that a report is made and that the agent felt that r best captured their relationship.[7] In addition, when the subject categorized her relationship with the recipient as "other," she was provided the opportunity to describe in more detail what the nature of the relationship was. These ranged from "Internet" to "boyfriend." We perform some ex post reclassification of this category below.

Each sender belongs to one of the two possible sample conditions j: C, which is the customer condition, or N, the noncustomer condition. We include fixed effects for both the week τ_t and the market μ_i. We particularly draw the reader's attention to the μ_i terms because they are meant to capture all systematic market-level factors including market size, competition, and store location. Although we expect the combination of these two sets of intercepts to capture most of the local and seasonal shocks, we also estimated specifications that include a year-earlier sales term $S_{i,\,t-52}^{B}$ to capture any recurrent shocks that might be seasonal *and* market specific.[8] Because this term is never significant and because the estimates of the other variables are qualitatively equivalent if this term is included, we do not report these results here.

Table 1 shows the summary statistics for the data, and Table 2 shows the pairwise correlations. Before presenting the results, it is important to caution against drawing any conclusions from Table 1 about the proclivity of customers versus noncustomers to create WOM. These data are market-level statistics and therefore reflect the different proportions of customers and noncustomers in each market. Finally, one sees in Table 2 that there is a fair amount of correlation within the customers and within the noncustomers, but little correlation across the conditions. The intracondition correlation is probably because of individual factors such as WOM episodes in which multiple people—friends, relatives, acquaintances—were informed at once, and the agent decided to separate the reports across relationship type.[9]

[7] Each report allowed only a single designation for r. For example, the agent could not report that she told a group of people made up of friends and acquaintances. She was allowed, however, to file two reports if she so chose.

[8] As an example in another domain, it might be the case that hotels in New Orleans have a large demand shock during Mardi Gras (February) each year, whereas no other markets would expect to see such a systematic shock.

[9] To check whether this intuition seemed reasonable, we ran a factor analysis on the 10 WOM variables ω_{ijt}^{r} for each market i in week t. This analysis yielded only two factors with eigenvalues greater than one. A follow-up factor analysis constrained to two factors using a varimax rotation revealed a pattern of loadings in which all of the customer variables loaded most heavily on one factor and all of the noncustomer variables loaded most heavily on the second factor. Details are available from the authors.

Table 2 Pairwise Correlations

	WOM customer to relative	WOM customer to friend	WOM customer to acquaintance	WOM customer to stranger	WOM customer to other	WOM noncustomer to relative	WOM noncustomer to friend	WOM noncustomer to acquaintance	WOM noncustomer to stranger
WOM customer to friend	0.36								
WOM customer to acquaintance	0.42	0.51							
WOM customer to stranger	0.26	0.57	0.41						
WOM customer to other	0.21	0.44	0.33	0.28					
WOM noncustomer to relative	−0.04	0.07	0.10	0.00	−0.07				
WOM noncustomer to friend	−0.02	0.11	0.08	0.19	0.11	0.22			
WOM noncustomer to acquaintance	0.04	0.13	0.08	0.07	0.08	0.31	0.61		
WOM noncustomer to stranger	0.00	0.05	−0.01	0.16	0.10	0.24	0.52	0.37	
WOM noncustomer to other	0.05	0.14	0.11	0.12	0.09	0.22	0.51	0.44	0.30

The results from our initial regressions are shown in Table 3.[10] In models (1)–(3), we present our analysis at different levels of aggregation of the WOM variables. In all models, we control for time and market effects. In model (1), we consider the overall amount of WOM (i.e., we form a variable $WOM_{it} = \sum_j (\sum_{r\in R} WOM^r_{ijt})$). Model (2) decomposes the WOM according to the sender's relationship to the firm: $WOM_{ijt} = \sum_{r\in R} WOM^r_{ijt}$. Model (3) reflects the completely disaggregated approach shown in Equation (1). Model (4) removes independent WOM variables that appear to have no explanatory power. Model (5) includes additional data as a follow-up to the main results.

We first consider the implications of the results in models (1)–(3) in Table 3. The first is that the firm can, it seems, create exogenous WOM among noncustomers that has a significant and measurable effect on sales. This can be seen in model (2). The coefficient on the WOM created by noncustomers suggests that each WOM episode yields average incremental category sales of \$192. Second, the results are also clear in reinforcing the message in Godes and Mayzlin (2004): All WOM is *not* created equal. Most important, this model shows that the impact of incremental exogenous WOM created by customers that have no relationship to the firm is significantly higher than the WOM created by customers. This provides initial support for H1. It is important to note that this does not mean that overall WOM by noncustomers is more impactful than that by customers. What it suggests is that firms interested in designing an exogenous WOM program—for example, refer-a-friend programs such as those investigated by Biyalogorsky et al. (2001)—should not confine themselves to their base of highly loyal customers. On the contrary, when the objective is to spread information, they may find less loyal customers to be more helpful.

The more detailed analysis in model (3) (Table 3) demonstrates that, consistent with the theory of weak ties (Granovetter 1973), WOM through acquaintances has significantly more impact than WOM to those with stronger ties in the social network such as friends or relatives. Thus, H2 is also supported. This argument, taken to its logical next step, would seem to suggest that WOM to strangers would be yet more powerful. However, there is likely to be an offsetting force associated with credibility that might render a suggestion from a stranger to be less credible. Note that this result is consistent with the results on job search reported by Granovetter (1973).

Given the apparent lack of explanatory power of the WOM variables other than customer-to-other WOM and noncustomer-to-acquaintance WOM, we performed a Wald test on the composite hypothesis that these eight other coefficients are all zero. This test could not reject the null ($F = 0.41$, $p = 0.91$). Thus, we estimate a third model in which—besides the market- and week-fixed effects—we include only customer-to-other WOM and noncustomer-to-acquaintance WOM. These results are shown in model (4) (Table 3). In this model, the effect size and significance level of the noncustomer-to-acquaintance WOM coefficient are increased, whereas those for the customer-to-other WOM coefficient are decreased.

These results begin to provide compelling evidence for the fundamental idea that focusing exclusively on loyal customers for a WOM marketing campaign may not be optimal. However, there are a number of important questions raised in these initial results that we address next. First, as a way of validating the results under a less stringent set of distributional assumptions, we reestimate models (2)–(4) (Table 3) via a bootstrap approach (see Table 2 in the Technical Appendix, found at http://mktsci.pubs.informs.org, for the summary of the results). These results show that even under far less stringent assumptions, there is support for our claim that less loyal customers may be more valuable to the firm in terms of their ability to

[10] In the aggregate model, we calculate the R^2 statistic for the differenced model. That is, the R^2 we report estimates the percentage of variance explained by the model *beyond* the market-fixed effects. The average R^2, if we include the market-fixed effects, is over 0.95 for all the models in the table. Note also that, although not shown, the week effects τ_t are included in the estimated model and are also reflected in the reported models' fit statistics.

Table 3 Aggregate Model Regression Results

Aggregate model—Fixed effects regression: $SALES_{i,t+1}$	(1)	(2)	(3)	(4)	(5)
WOM overall to anyone	64.63				
	0.90				
WOM customer to anyone		−55.16			
		−0.55			
WOM noncustomer to anyone		192.00 **0.066**			
		1.85			
WOM customer to relative			−34.39		−167.44
			−0.04		−0.20
WOM customer to friend			−267.07		−260.90
			−1.28		−1.24
WOM customer to acquaintance			−1.77		84.81
			0.00		0.23
WOM customer to stranger			−91.61		−106.16
			−0.25		−0.29
WOM customer to other			662.85 **0.032**	571.50 **0.052**	
			2.17	1.96	
WOM customer to other (online)					2,039.08 **0.069**
					1.83
WOM customer to other (not online)					366.45
					1.12
WOM noncustomer to relative			299.83		118.48
			0.47		0.18
WOM noncustomer to friend			153.07		130.23
			0.60		0.51
WOM noncustomer to acquaintance			907.42 **0.038**	1,011.1 **0.007**	867.56 **0.052**
			2.10	2.73	1.96
WOM noncustomer to stranger			−180.37		−191.56
			−0.56		−0.59
WOM noncustomer to other			−122.23		
			−0.37		
WOM noncustomer to other (online)					−708.99
					−0.98
WOM noncustomer to other (not online)					68.3989
					0.18
N	180	180	180	180	180
R^2	0.239	0.253	0.305	0.289	0.309
F-test: All coefficients $= 0$	4.01	3.97	3.01	4.75	2.760
$\Pr > F$	0.000	0.000	0.000	0.000	0.000

Notes. t-statistics are presented below the coefficient estimates. For all coefficients with p-values below 0.10, the p-value is presented in bold next to the estimate.

create meaningful, incremental WOM. In the reestimated model (2) (Table 3), the crucial test of our theory in which customers and noncustomers are compared, the noncustomers' WOM is significant at the $p < 0.05$ level. The noncustomers' WOM is not significant at the $p < 0.10$ level when all possible WOM variables are included (see the reestimated model (3) in Table 3), but when we exclude those that have no explanatory power, the noncustomers' WOM does achieve significance. So these bootstrap estimates provide further evidence for the robustness of our results.

Another aspect of our results requiring additional analysis is the impact of customers' WOM to the "other" category, which was somewhat unexpected ex ante. In an effort to better understand the source and nature of this impact, we analyzed in detail the free text reports submitted with each WOM report. To do so, we hired two raters who were not informed about the goals of the study to use this free text to classify each of these "other" reports into either one of six categories represented by the four existing categories (friend, relative, acquaintance, stranger), an "online" category, or an "indeterminate" category. To resolve disagreements (the ex post classified "friend" and "acquaintance" categories had 50% and 35% agreement rates, respectively), the raters discussed the disputed reports in person. However, they were unable to reach agreement on many disputed reports, indicating the highly subjective nature of the ex post classification task into these categories. About 30% were categorized as "online." Among these, the raters had a 90% agreement rate. Given this, we decided to separate the "other" category into "other online" and "other not online." We reran the model and present the results through model (5) in Table 3. Notably, the coefficient on noncustomers' WOM to acquaintances is hardly affected by this analysis, though the effect size is slightly lower. Clearly, there seems to be a very large effect of WOM created online by customers, though the same is not true with respect to noncustomers. The fact that customers' WOM has a large effect online but not offline may be viewed as quite consistent with the network explanation we offer above. That is, the chain's customers were probably more likely to have spread WOM offline than online prior to the start of the campaign. Hence, the marginal effect of an informative WOM episode from a customer would be higher online than offline. This is a preliminary and ex post finding and needs to be interpreted with caution, but it certainly suggests that all exogenous WOM created by loyal customers is *not* meaningless. On the contrary, it may suggest that the nature of the impact of loyal customers' WOM may be different from that of less loyal or noncustomers. Clearly, this would not explain why the noncustomers' online WOM was not effective while their offline WOM was. One hypothesis might be that customers—by virtue of their deeper experience with and interest in the category—are better at identifying the communities in which this particular category is discussed. This again suggests that the nature of the WOM—not just the size of the impact—generated by loyal customers and noncustomers may be different. Further research is needed to explore this interesting issue.

As noted above, some of the noncustomers had previous experience generating WOM for the agency's other clients. This raises potential questions about the source of the results we present here. Recall that our claim is that the result is driven by the fact that the social networks of loyal customers are already well informed about the firm whereas those of less loyal customers—or, in this case, noncustomers—have not been informed. It is possible, however, that the source of some or all of the "noncustomer" effect is their experience with WOM generation. Before discussing the results of our empirical analysis of this issue, we note that there are good reasons to believe that the impact of the noncustomers' experience may not be substantial. First, we suggest that these agents should not be thought of as "professional WOM creators." In fact, they receive little or nothing for their efforts, nor are they rewarded directly for the impact of their recommendations (i.e., there is nothing like a "commission" plan). They do receive points for their reports but the points are awarded as much for the originality of their ideas and the richness of their feedback as for any projected impact.[11] Finally, we would expect that the true expertise associated with identifying opportunities for recommending the firm and with providing a rich description of the firm should have been significantly greater for the firm's loyal customers. After all, creating WOM is hardly a unique and rare technical skill where one would expect to observe significant experience effects. However, to ensure that our results do not stem from the omission of an experience variable, we reestimated model (2) of Table 3,[12] controlling for the number of previous campaigns the agents had worked on. We did so in several ways. First, we split the WOM episodes generated by noncustomers into two separate variables: those generated by agents who had previously participated in a campaign and those who had not. Second, we further disaggregated the noncustomer WOM data by estimating a separate coefficient for the WOM generated by the agents who had participated in zero, one, two, three, and four campaigns. The results were consistent across these approaches. First, in neither case were any of the WOM coefficients significant at a $p < 0.10$ level (in comparison to model (2) in which the noncustomer WOM coefficient is significant). Second, a Wald test in each case fails to reject the null hypothesis that the coefficients across the different noncustomer WOM variables are all equal. Finally, both AIC and BIC statistics favor the simpler model (2) over both of these models. Thus, though we cannot rule out completely the possibility that noncustomers had some useful experience, the data suggest that this is not driving our reported results.

Although our theory concerns the relative loyalty of those creating WOM for the firm, the two populations in this data set have clear differences both observable and unobservable that one must attempt to account for to the extent possible. In addition to the different experience levels, the firm's customers—as a result of having a deeper experience level with the product—might offer recommendations that are more multifaceted, containing possibly some mixed or negative information. On the other hand, the firm's customers—having had more conversations about the firm's products already—might have less intrinsic motivation to provide a convincing recommendation.[13] To test more completely our theory and in an

[11] Indeed, the number of points awarded had no explanatory power in any of the several specifications of the sales model in which we tested it.

[12] These results are available from the authors.

[13] We thank two anonymous referees for suggesting these possibilities.

attempt to demonstrate the robustness of our results while controlling for important factors, we provide two additional analyses. First, we estimate a similar model to that above, including only the firm's customers and stratifying them according to a behavioral loyalty measure. Then, in the section that follows, we implement an online experiment to more fully control the context.

4.1.1. Loyalty-Based Stratification. To analyze the impact of loyalty within the firm's set of customers, we create quartiles based on each customer's past visits to the chain: Q1 is the quartile with the most visits and Q4 has the fewest. Note that whereas the number of store visits is a behavioral measure of loyalty, our online study that follows in §4.2 will include an attitudinal component as well. Our discretization of the continuous visit data into buckets captures the idea that the impact of customer loyalty often occurs in a nonlinear fashion. For example, Bowman and Narayandas (2001) find differences in WOM behavior between the highly loyal and the rest of the population following a customer-initiated contact with the company, Krishnamurthi and Raj (1991) find significant differences in price sensitivities between loyal and nonloyal segments, and Neslin et al. (1985) find that the promotional acceleration effect was bigger for heavy users than for light users. Finally, we believe it also captures the way most firms think about their customers. The creation of loyalty buckets or segments is a common approach in customer relationship management and the customer lifetime value literature (Hartmann and Viard 2008, Rust and Verhoef 2005, Gupta et al. 2006a). In fact, as outlined above, the firm involved in this study recruited participants for the campaign by segmenting their customers according to this measure of loyalty.

See Table 3 in the Technical Appendix, found at http://mktsci.pubs.informs.org, for summary statistics on these constructed quartiles. Members in Q4 are those who joined the loyalty program immediately prior to the beginning of the campaign. We then interact the quartile number with the WOM variables to create quartile-specific WOM measures. Because we also include a noninteracted term in the specification (WOM to anyone), we interpret the interactions as the difference in the impact of WOM on sales as a function of the relative behavioral loyalty of the sender. The results are shown in Table 4. We include several specifications to test the robustness of the results. Note that among those models shown in Table 4, model (4) is preferred based on a Wald test as well as common information criteria.

What these results show is that in some cases, the impact of WOM from customers in the loyalty program is higher the less loyal that customer is (see the significant impact of WOM created by Q4 members to acquaintances). Most importantly, it is *never* the case that the most loyal customers—those in Q1—deliver the most impactful WOM. These results provide some additional strength behind our claim that the firm should consider designing WOM campaigns not just for their highly loyal longtime customers but also for their newer and less loyal customers. These results also suggest that the results found in Table 3 do not stem entirely from unobservable differences between experienced and inexperienced noncustomers. These results also further reinforce the idea that if the firm wants to create impactful WOM, then WOM to acquaintances should be the target. In Table 3, we saw that noncustomers created impactful WOM to acquaintances. In Table 4, we see that, similarly, less loyal customers also created impactful WOM primarily via discussions with their acquaintances.

4.2. Experimental Investigation

In this section, we replicate our core results in an experimental setting to avoid the unobservable differences between populations that commonly exist in field tests without random assignment. This also allows us to investigate the mechanism behind the key finding that less loyal customers spread more impactful WOM. The mechanism we propose in §2.1 is that less loyal customers' friends and acquaintances are less likely to be aware of and loyal to the product. This increases the marginal impact of a new recommendation. One shortcoming of the field test data is that it does not allow us to test the assumptions behind the hypothesis because we only have access to the recommender's loyalty and not the loyalty of others in the network. The experimental setting allows us to collect data on both sides of a WOM episode.

We recruited subjects from a university subject pool to participate in a study of website usage. Because our proposed mechanism requires the existence of past relationships and interactions, we asked each participant to recruit two friends to participate in the study as well. These three then formed a "group" for the purpose of the study. The study had two phases. In the first phase, the subjects took an online survey that elicited their current preferences for six news and entertainment websites: Google News, Slate, Friendster, Smoking Gun, Slashdot, and PostSecret. We asked each subject whether they had heard of the site (yes/no), whether they had visited it (yes/no), whether they visit it regularly (7-point scale), whether they intend to visit it (7-point scale), and whether they would recommend the site (yes/no). See Appendix A to review the questions used. In the second phase of the study, which took place six days after the first phase, each subject was given a recommendation from another person in their group. For example, upon logging in, Linda was told, "Dan (dan@yahoo.com) recommends Slate." Hence, in this instance, Dan is the

Table 4 Aggregate Model Regressions—Loyalty Quartiles

Aggregate model—Fixed effects regression: $SALES_{i,t+1}$	(1)	(2)	(3)	(4)
WOM customer to anyone	−4,871.12	−4,191.63	−182.28	−125.81
	−1.63	−1.42	−1.33	−1.62
WOM noncustomer to anyone	144.99			
	1.29			
WOM noncustomer to acquaintance		1,071.42 **0.013**	986.00 **0.009**	1,232.52 **0.002**
		2.51	2.64	3.13
WOM customer to relative—Q2	2,704.59	1,851.93		
	0.90	0.62		
WOM customer to relative—Q3	5,313.25	5,110.02		
	1.43	1.40		
WOM customer to relative—Q4	5,620.70	4,742.66		
	1.62	1.38		
WOM customer to friend—Q1	4,488.88	3,996.62		
	1.60	1.45		
WOM customer to friend—Q2	4,675.30	3,878.45		
	1.55	1.30		
WOM customer to friend—Q3	5,082.47 **0.098**	4,185.59		
	1.67	1.38		
WOM customer to friend—Q4	4,345.32	3,449.01		
	1.44	1.15		
WOM customer to acquaintance—Q1	4,574.88	3,811.72	−367.52	
	1.42	1.20	−0.63	
WOM customer to acquaintance—Q2	4,295.65	3,608.80	−524.75	
	1.32	1.12	−0.52	
WOM customer to acquaintance—Q3	4,272.24	3,859.66	137.24	
	1.39	1.27	0.19	
WOM customer to acquaintance—Q4	6,068.66 **0.055**	5,568.69 **0.074**	1,370.44 **0.051**	1,176.62 **0.072**
	1.94	1.80	1.97	1.81
WOM customer to stranger—Q1	5,008.88	4,500.60		
	1.59	1.45		
WOM customer to stranger—Q2	4,662.46	4,068.89		
	1.52	1.35		
WOM customer to stranger—Q3	4,412.93	4,203.13		
	1.46	1.41		
WOM customer to stranger—Q4	4,779.85	4,085.22		
	1.41	1.22		
WOM customer to other—Q1	4,493.00	3,639.18	−35.36	
	1.48	1.21	−0.07	
WOM customer to other—Q2	6,941.09 **0.024**	6,268.31 **0.039**	2,311.85 **0.000**	2,171.94 **0.000**
	2.28	2.08	4.19	4.13
WOM customer to other—Q3	4,447.92	3,914.74	−72.59	
	1.41	1.26	−0.10	
WOM customer to other—Q4	3,420.05	3,528.29	314.56	
	1.19	1.25	0.21	
N	180	180	180	180
R^2	0.378	0.399	0.367	0.354
F-test: All coefficients $= 0$	2.52	2.75	3.98	5.49
$\Pr > F$	0.0000	0.0000	0.0000	0.0000

Notes. t-statistics are presented below the coefficient estimates. For all coefficients with p-values below 0.10, the p-value is presented in bold next to the estimate.

sender and Linda is the *receiver* of a recommendation. After a brief unrelated task, we collected the same preference and awareness measures about each of the six sites that we had collected in the first phase.

The experimental manipulation was to randomly assign each subject either to a *high_loyalty* or a *noncustomer* condition based on the initial loyalty of the *sender* of the recommendation they received. That is, some subjects received recommendations from senders who were highly loyal to a site and others received recommendations from senders who were not users of the site. The manipulation was based on

Table 5 Congruence of Loyalty and Awareness Within a Social Network

Site	Pr[aware | sender aware] (%)	Pr[aware | sender unaware] (%)	Correlation between senders' and receivers' loyalty	Correlation within person of loyalty and recommendation
Smoking Gun	92.86	45.83***	0.628***	0.680***
Slate	64.00	19.12***	0.420***	0.809***
Slashdot	39.13	21.13*	−0.099	0.843***
PostSecret	44.44	17.65***	0.314**	0.872***
Google News	87.34	75.00	0.580***	0.532***
Friendster	86.67	50.00***	0.487***	0.831***

$^{*}p < 0.10$, $^{**}p < 0.01$, $^{***}p < 0.001$.

the sender's initial loyalty (phase 1) to the recommended site. We define loyalty as the average of two items from the survey: "I regularly visit the site" and "I intend to visit/keep visiting this site." Each of these was measured on a 7-point Likert scale:

$$Loyalty_{ijt} = \begin{cases} (Vis\_reg_{ijt} + Intent_{ijt})/2 \\ \quad \text{if } i \text{ visited } j \text{ prior to time } t, \\ 0 \quad \text{otherwise}, \end{cases} \tag{2}$$

where $t \in \{1, 2\}$ is the phase of the study. Note that this measure of loyalty combines a frequency component as well as an attitudinal component. We define the *high_loyalty* state as $Loyalty_{ij1} \geq 6$ and the *noncustomer* state as $Loyalty_{ij1} = 0$. For example, suppose that Dan (the sender) has a loyalty of 6 to Slate and had never visited Friendster. If his friend Linda (the receiver) is randomly assigned to the *noncustomer* condition, she receives a recommendation for Friendster from Dan. If, however, she is in the *high_loyalty* condition, she receives a recommendation for Slate from Dan. When several sites fit the criteria, we picked a site at random. Note that though this dichotomy is similar to the initial analysis of the field test where we compare the effectiveness of members of the firm's loyalty program and noncustomers, here the difference between the two groups is further amplified because we compare *very* loyal customers to noncustomers. Moreover, it is important to notice that whereas the loyalty levels of the sender are *measured*, the condition into which each receiver is assigned is manipulated randomly, making this a true experiment.[14]

The six sites were pretested on a different sample to ensure similar average loyalty levels (see Table 4 in the Technical Appendix, found at http://mktsci.pubs.informs.org, for the average loyalty levels for the experimental sample). We excluded Google News from the set of possible recommendations because in our sample it had a much higher level of awareness than the other sites. We obtained 96 usable responses.[15] The distribution of recommended sites is given in Table 5 in the Technical Appendix, found at http://mktsci.pubs.informs.org, the distribution of recommendations is weighted toward Friendster and Smoking Gun, the sites that enjoyed a relatively higher awareness in our sample. This is partly due to the fact that a respondent unfamiliar with a site would often leave all of the questions related to that site blank, which meant that we could not sample it for a recommendation.

Before presenting our main results on the change in preferences, we first investigate a crucial assumption behind our theory. As argued above, we expect that a customer's social circle is likely to be aware of the same products that she is aware of and loyal to the same products she is loyal to. We are now able to test for this directly. As Table 5 in this paper shows, for all sites but Google News receivers' phase 1 awareness levels of sites is significantly higher when the sender—someone in their social circle—is aware of the site. It may not be surprising ex post that Google News yields only directionally consistent results: The awareness levels are so high that this may be the result of a ceiling effect because Google News has the highest average awareness levels of all of the sites investigated. Similarly, Table 5 demonstrates that the phase 1 loyalty levels of the sender and the receiver are positively correlated in all sites but Slashdot. Another important element of our theory is that one talks about the products to which one is loyal. As a result, the network of a highly loyal customer is saturated, offering fewer incremental gains from a WOM campaign. As shown in Table 5, not surprisingly, the willingness to recommend is highly correlated with loyalty for each of the

[14] We preferred this design to an obvious alternative in which recommendations are for a single site. In this alternative design, we would still be able to measure loyalty and we would expect there to be variance in loyalty levels across people, but we would not be able to randomly manipulate the condition to which each subject would be assigned.

[15] We discarded responses for three reasons: (1) if data were missing on questions related to the recommended site, (2) if the subject took an unreasonably short amount of time to complete the task, or (3) if the responses were inconsistent across phases (e.g., at $t = 1$ the respondent indicated that she had visited the recommended site before, but at $t = 2$ she indicated that she had not visited the site before).

Table 6 Experimental Results

Dependent variable: Change(intention to visit recommended site)—Change(average intention to visit other sites) for receiver				
	(1)	(2)	(3)	(4)
Recommender high loyalty	−0.630 **0.079** −1.78	−0.719 **0.052** −1.97	−0.166 −0.45	−0.047 −0.12
Friend		0.426 1.03	0.590 1.53	0.760 **0.054** 1.93
Receiver heard about site at $t=1$			−1.692 **0.000** −3.92	
Receiver's loyalty to site at $t=1$				−0.248 **0.000** −3.85
No. of observations	96	96	96	96
R^2	0.0325	0.0435	0.1802	0.1759
F-test: All coefficients = 0	3.15	2.11	6.74	6.55
Pr > F	0.079	0.127	0.000	0.000

Notes. The t-statistics are presented below the coefficient estimates. For all coefficients with p-values below 0.10, the p-value is presented in bold next to the estimate.

websites in the sample (where the correlation ranges from 0.532 to 0.872). Combined, these results support our assumption of congruity of awareness and loyalty within a social network.

We next turn to our main results. We are interested in the effect of a recommendation on the *change* in the receiver's intention to visit the recommended site. We choose this particular measure because (i) in this context the number of visits is the relevant sales measure, (ii) the difference in intention allows us to measure the marginal impact of a recommendation, and (iii) the measure differences out individual- and site-fixed effects stemming from differences in awareness or popularity, for example. Because there is a time gap between the two phases, we also need to control for the possibility that there are individual differences in the phase-to-phase changes. We use the following dependent variable in the analysis:[16]

$$\Delta Intent_i \equiv (Intent_{i\hat{j}2} - Intent_{i\hat{j}1}) - \frac{1}{5}\sum_{j\neq\hat{j}}(Intent_{ij2} - Intent_{ij1}),$$

where $\hat{j}$ is the site about which i receives a recommendation. The first term in parentheses captures i's change in intention to visit the recommended site, and the second term captures her average change in intention (note that the recommended site is excluded in the second-term average). The focus of our analysis is an assessment of the impact of the loyalty of the recommender (i.e., the sender) on the change in intention of the receiver following the recommendation. Thus, in our core analysis we regress $\Delta Intent_i$ on the sender's loyalty level (our experimental manipulation). In addition, we control for the nature of the relationship between the sender and the receiver (a dichotomous variable equal to one for friends and zero for acquaintances).[17]

Our results are in Table 6. In model (1) of Table 6, we see that the marginal effect of WOM is lower when it comes from a highly loyal customer. A recommendation by a noncustomer results in $\Delta Intent$ that is 0.63 higher (nearly 400% relative to the mean) than a recommendation by a highly loyal customer.[18] Perhaps not surprisingly, controlling for the nature of the relationship increases the effect of the recommender's loyalty (see model 2, Table 6).[19]

To investigate further the underlying mechanism at work, we control in models (3) and (4) (Table 6) for whether the receiver had heard of or been loyal to the site, respectively. Recall that our theory is based on the idea that less loyal customers are effective because their network is more likely to consider information about the product to be new. Thus, when this is not the case—when the receiver is aware of or loyal to

[16] We prefer to control for possible individual-level intention changes in this way rather than by including the other site intention change measures as independent variables because of concerns about the endogeneity that might arise in such an analysis.

[17] According to our instructions, a subject was asked to recruit two friends who were acquainted with (i.e., not friends with) each other. This formed our initial classification. However, we were concerned that the recruiter may be misinformed about the relationship between the other two members of the group. Thus, we also directly asked each subject how often she interacted with the recommender. In cases where the subject indicated that she interacted weekly with the recommender but our initial designation was "acquaintances," we reclassified the relationship to "friends"; i.e., we used a respondent's own characterization of her relationship with another, not that of her friend who may have recruited them both into the study.

[18] The receiver intention change variable has a mean of 0.17.

[19] This finding must be interpreted with caution, however, given the low value of the F-statistic.

the product—we should not expect the result to hold. As shown in models (3) and (4) in Table 6, consistent with our expectation, when controlling for a receiver's awareness or loyalty the negative effect of a recommender's loyalty disappears. For example, following model (4) in Table 6, a change in a receiver's loyalty from 4 to 6 results in decrease in $\Delta Intent$ of 0.50. This reinforces the point that the firm should consider targeting less loyal customers to spread information about its products. Clearly, if possible, the firm would like to target uninformed customers to be receivers of messages. However, this is in practice very difficult to do. What these results suggest is that using less loyal customers to "spread the word" may be a useful proxy for the state of information in their networks.

Notably, in this final specification the recommendation of a friend is more influential than the recommendation of an acquaintance, which seems to contradict the earlier result that the word of mouth to an acquaintance is especially powerful. One possible explanation for this is that there are two forces at work here: (i) The network effect (the preferences of an acquaintance are less correlated with one's own preferences, which would make a recommendation more powerful), and (ii) the persuasiveness effect (the recommendation of a friend is inherently more persuasive). By including the receiver's loyalty in the specification in model (4), we are controlling for (i), the network effect that—in the field test—may have dominated the second effect.

In conclusion, our field test and follow-up experiment suggest that recruiting less loyal customers as recommenders allows the firm to reach less aware and less loyal consumers whose intentions may be more easily influenced. From a managerial perspective, this argues that having less loyal customers as participants in a word-of-mouth marketing campaign may in some cases deliver a higher marginal benefit to the firm.

5. Do Opinion Leaders Create WOM That Matters?

In this section, we follow up on the key insight that the firm's focus in a WOM campaign should be on less loyal customers or perhaps even noncustomers. We note again that this is not necessarily a statement about the overall impact of WOM but only about the creation of marginal or incremental WOM over and above what is being created already. Our interest in this section is in determining to what extent and how the firm can identify those customers that will most likely create this highly impactful type of WOM. In particular, we are interested in the usefulness of selecting for inclusion in a WOM marketing campaign those who are considered to be "opinion leaders."

H3 proposes that with respect to WOM creation, there exists an interaction between opinion leadership and the customer's loyalty to the firm: among loyal customers, opinion leaders create more WOM than average but the same may not be true among less loyal customers. As in §4.1, we use our field data to test this hypothesis in two ways: (1) We compare the effect of opinion leadership between customers and noncustomers, and (2) within the firm's customers, we look for an interaction between the degree of behavioral loyalty and opinion leadership.

The dependent variable is WOM_k, the number of WOM episodes reported by individual k. Because the dependent variable is a nonnegative integer, we estimate a count model. We make the standard assumption of exponential mean parametrization (see Cameron and Trivedi 1998):

$$\mathrm{E}[WOM_k] = \mu = \exp(x\beta). \tag{3}$$

We then estimate a negative binomial regression model, which allows for a test of overdispersion. For the noncustomers, we estimate the following model:

$$\mathrm{E}[WOM_k] = \mu = \exp\Big(\beta_1 \cdot AGE_k + \beta_2 \cdot FULLTIME_k + \beta_3 \cdot OL_k + \sum_{i=2}^{15} \mu_i + \sum_{l=1}^{4} u_l + \varepsilon_k\Big). \tag{4}$$

We consider both the overall number of episodes as well as those WOM episodes involving only acquaintances because our results in §4 as well as the extant literature suggest that WOM to acquaintances may be especially impactful. We present the results for WOM to acquaintances in the main body of the paper, and we present the results for overall number of episodes in Table 7 in the Technical Appendix, available at http://mktsci.pubs.informs.org. OL_k is k's "opinion leadership" score. As part of the survey instrument in the original field test, we administered the King and Summers (1970) scale (see Appendix B for a sanitized version of the scale we implemented). As with previous studies, we found this scale to be of adequate reliability ($\alpha = 0.79$). Given the group-level differences shown in Table 1 in the Technical Appendix, found at http://mktsci.pubs.informs.org, it is important to control for AGE_k, $FULLTIME_k$ (a dichotomous variable equal to one when respondents work full time) as well as how often they eat out. Given the discrete nature of our data for the latter, it is included as a set of dummies u_l.[20] One would imagine that other demographic variables—gender and income, for example—might be predictive of WOM behavior in specific categories.

[20] Specifically, our data were collected on a 5-point semantic scale in response to the question, "How often do you go out to eat?" The scale items were as follows: all the time, a lot, occasionally, rarely, and never. No subjects indicated "never."

Table 7 Individual Model Results (WOM to Acquaintance)—Negative Binomial Regression

	Dependent variable: WOM to acquaintance					
Sample	(1)	(2)	(3)	(4)	(5)	(6)
	Noncustomers	Customers				Combined
Age	−0.03	−0.03	−0.04 **0.025**	−0.04 **0.026**	−0.04 0.026	−0.03 **0.027**
	−1.52	−1.64	−2.24	−2.22	−2.22	−2.20
Work full time	−0.22	−0.12	−0.01	−0.02	−0.02	−0.12
	−0.71	−0.30	−0.02	−0.06	−0.06	−0.51
Eat out a lot	−0.83 **0.00**	−0.43	−0.36	−0.38	−0.38	−0.57 **0.023**
	−2.87	−1.01	−0.89	−0.93	−0.93	−2.27
Eat out occasionally	−1.28 **0.001**	−0.06	0.02	0.06	0.06	−0.59 **0.053**
	−3.32	−0.11	0.04	0.12	0.12	−1.93
Eat out rarely	−14.87					−17.49
	−0.01					0.00
Opinion leadership	0.30	0.90 **0.043**	0.76 **0.077**	0.29	0.78 **0. 076**	0.29
	1.03	2.03	1.77	0.57	1.77	1.13
$Q1$				−7.65 **0. 08**	0.71 **0.058**	
				−1.75	1.90	
Opinion leadership × $Q1$			0.22 **0.008**	1.98 **0.050**	1.98 **0.050**	0.27 **0.000**
			2.66	1.96	1.96	3.76
N	670	378	378	378	378	1,048
Centered variables	N	N	N	N	Y	N
Log likelihood	−233.59	−207.20	−203.80	−202.10	−202.10	−459.68
LR-test: All coeffs. = 0	52.93	29.09	35.90	39.290	39.290	58.670
Pr > χ^2	0.00	0.09	0.02	0.01	0.01	0.00
LR-test: $\alpha = 0$	9.88	61.57	47.82	48.78	48.78	83.36
Pr > χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Notes. z-statistics are presented below the coefficient estimates. For all coefficients with p-values below 0.10, the p-value is presented in bold next to the estimate.

However, we did not have access to any demographic data other than those that we report here. We again include market-level fixed effects μ_i.

For our analysis of customers stratified by their behavioral loyalty, we estimate

$$E[WOM_k] = \exp\bigg(\beta_1 \cdot AGE_k + \beta_2 \cdot FULLTIME_k + \beta_3 \cdot OL_k + \beta_4 \cdot OL_k * Q1_k + \sum_{i=2}^{15}\mu_i + \sum_{l=1}^{4} u_l + \varepsilon_k\bigg), \tag{5}$$

where $Q1$ is again a dummy indicating that the customer is in the quartile demonstrating the highest level of behavioral loyalty. Our key variable of interest in this equation is $OL_k * Q1$, the interaction between opinion leadership and loyalty.

We investigate the impact of these individual-level characteristics on one's creation of WOM both overall (Table 6 in the Technical Appendix, found at http://mktsci.pubs.informs.org) and specifically to acquaintances (Table 7 in this paper). First, note that a likelihood ratio test rules out the null hypothesis of equidispersion (mean equal to variance or "$\alpha = 0$" in the tables) at $p<0.01$. Hence, the negative binomial model is preferred to the Poisson model. Also, note that our results are qualitatively identical if we ignore the fact that we have counts data and use linear regression instead.

Using the data on WOM to acquaintances, we test H3 in a number of ways. The results are shown in Table 7. First, we compare estimates of Equation (4) on the noncustomer and the firm's customer samples. (That is, we compare model (1) to model (2) in Table 7.) We see that opinion leadership is significant in the customer sample and is not significant in the noncustomer sample. We then further investigate whether we find a similar pattern within the customer sample once customers are stratified by their loyalty level: We estimate Equation (5) on the customer sample (see model (3) of Table 7). Note that we still see the main effect of opinion leadership on WOM generation in the customer sample: OL_k is still positive and significant in model (3). We also find that the interaction term $OL_k * Q1_k$ is positive and significant. That is, we find that (a) in the noncustomer population, opinion leaders do not produce more WOM than nonopinion leaders, (b) in the customer population, opinion leaders do produce more WOM than nonopinion leaders, and (c) the effect of opinion leadership is increasing in a customer's loyalty. Combined, these results provide support for H3.

As an additional robustness check, we also estimate the main effect of loyalty (see model (4) in Table 7). In model (4), $OL_k * Q1_k$ is positive and significant but the main effect of OL_k is not significant. Unfortunately, this specification suffers from a multicollinearity problem because the correlation between $OL_k * Q1_k$ and $Q1_k$ is 0.99, which makes it very difficult to estimate the parameters simultaneously. For this reason, we center the $Q1_k$ and OL_k variables around their means (see model (5) in Table 7). This does not change the interaction result from model (4), but we see that the main effect of OL_k is now significant as in model (3) (Table 7).

Finally, we attempt to combine customers and noncustomers into a single sample. The complication in doing this is that the latter have no "visits" with which to construct quartiles. Nonetheless, a natural way to handle this is to simply include the noncustomers in the lowest quartile and reestimate the model using all of the subjects together. These results are shown in model (6) of Table 7 and are again consistent with H3. To illustrate the magnitude of the interaction effect, consider the following example based on the estimated coefficients in model (6) of Table 7: An agent who scores a 6.5 out of 7 on the opinion leadership scale (and is at the mean values of all other variables) generates 0.24 more WOM episodes per week if he is in the upper quartile on the loyalty scale than if he is in the lower three quartiles.[21] Hence, these results suggest that selecting only those high on opinion leadership would potentially be a serious error because it might identify only those *loyal* customers willing to create WOM and not the crucial *less loyals*.

The results on overall WOM (see Table 6 in the Technical Appendix, found at http://mktsci.pubs.informs.org) are qualitatively similar to the results on WOM to acquaintances. The only notable qualitative difference is that when we include the main effect of $Q1_k$ (see models (4) and (5) in Table 6, in this paper), the interaction term $OL_k * Q1_k$ is not significant. However, the fit measures slightly though consistently favor the more parsimonious model (3) over models (4) and (5).

Hence, our analysis in §4 suggests that less loyal customers should be recruited to participate in a WOM campaign. Their recommendations are more likely to be received by people who are currently less experienced with or less informed about the firm's products. However, we find here that while opinion leadership is associated with higher WOM creation for very loyal customers, it is less true for less loyal customers. In fact, it may not hold at all for the less loyal customers (see model (6) in Table 7). We leave it up to future research to explore metrics that would identify key disseminators of WOM among less loyal customers.

6. Conclusion

This paper represents the first attempt, to our knowledge, to explicitly test whether and how the firm should attempt to create exogenous WOM to drive sales. On one hand, the news seems to be good. We have shown that in some cases, purely exogenous WOM is associated with higher week-to-week sales. Thus, the examples we cite at the outset of the paper—and the hundreds of other firms following a similar path—may represent a rational and profit-maximizing solution to the promotion problem. Moreover, we have shown that for products with low or moderate initial levels of awareness, loyal customers are not necessarily the cornerstones of a successful WOM campaign. In fact, we have argued that because the loyal customers' networks have probably been informed about the product for some time, the incremental WOM created by the campaign may have little impact. In this sense, our study differs from most earlier studies on WOM in that we investigate the WOM surrounding existing products on the market rather than novel new offerings. The "bad news," however, is that although our results suggest that the firm should be using its less loyal customers to create WOM, it may not be able to rely on the popular opinion leadership scale to identify the most effective, less loyal disseminators of WOM.

6.1. Limitations

The paper has a number of important limitations that should suggest to the reader that these results might best be viewed as starting points for further research. Some of the most important limitations that we have previously alluded to have to do with the field test portion of the paper. First, it is very difficult to control for all the differences between the customer and the noncustomer populations. In fact, one concern is that the agent population may be more experienced and, hence, more persuasive on average whereas the customer population may give more nuanced information about the firm, which may render it less persuasive. In fact, we have no information on the valence of the recommendations. Although we assume that most recommendations are positive because of the nature of the campaign, we would expect that differences in valence would account for some of the variance in effectiveness. Second, we have no way to ascertain that any of the WOM episodes have actually taken place. If this were a major problem, of course, it would likely bias toward a nonsignificant result. Nonetheless, it is an issue that is encountered by both researchers and practitioners alike in this area. Third, a large portion

[21] For this nonlinear model, the marginal impact of a variable is calculated as follows: $\partial \mathrm{E}[Y \mid X]/\partial X_j = \beta_j \exp(x'\beta)$.

of the data that we collect is self-reported and incomplete. For example, we would have liked to have collected information on recommenders' income and gender.

6.2. Future Research

The paper identifies a number of interesting areas on which future research projects could focus. First and foremost, one needs to replicate these results in other categories. The product area is a relatively low risk one and, thus, the simple transfer of information ("Hey, have you ever heard of ___?") is probably sufficient to generate trial. In other categories—particularly those in which there is more risk associated with purchase—the lower brand-level knowledge of noncustomers may mitigate the network effects we have demonstrated here.

The other clear opportunity for deeper investigation lies in the exploration of measures to identify disseminators of WOM among less loyal customers. One possibility is to explore existing measures such as extraversion. Another possibility is to identify new measures that have to do with the disseminator's network. Given the clear impact of King and Summers (1970), the rewards to such an endeavor would appear significant.

Although we have attempted in our online experiment in §4.2 to not only replicate our field results but also to shed some light on the mechanism, this investigation is not strictly a test of the underlying process. Future research focused on differentiating our proposed mechanism for this phenomenon from others would be valuable.

An aspect of the WOM creation process with which this paper does not deal is the question of tactics. Given whom we should be targeting and how we might be able to find them, what should the firm do to encourage them to go out and tell people about the firm? Options range from monetary refer-a-friend programs to recognition programs and beyond. One could imagine that an experimental approach to this problem would yield interesting and useful results. In fact, this paper does not address but raises interesting issues about incentives. Clearly, one of the key differences between loyal and nonloyal populations is the issue of intrinsic incentives. However, we do not address how extrinsic and intrinsic incentives compare in encouraging WOM production.

Finally, we did not address the competitive aspects of the WOM creation problem. Once one considers the possibility of a competitor, this problem becomes even more complicated. How can the firm, for example, enlist its customers to "switch" another firm's loyal customers to its side? Would the same implications found here—that nonloyal customers are the key—still hold in such a setting? The answers to these questions are not at all clear ex ante but would be of great interest both practically and theoretically.

Appendix A

1. I have heard of this site: Yes–No–N/A
2. I have visited this site: Yes–No–N/A
3. I regularly visit this site: (1–strongly disagree to 7–strongly agree)–N/A
4. I intend to visit/keep visiting this site: (1–strongly disagree to 7–strongly agree)–N/A
5. I would recommend this site: Yes–No–N/A

Appendix B

Opinion Leadership Scale

Note that all items were measured on a 7-point scale.

1. In general, I like to talk to my friends and neighbors about category (7–very often to 1–never).
2. Compared with my circle of friends, I am ______ to be asked about category (7–not very likely to 1–very likely).
3. When I talk to my friends about category, I (7–give a great deal of information to 1–give very little information).
4. During the past six months, I have told ____ about category (7–no one to 1–a lot of people).
5. In discussions about category (7–my friends usually tell me about category to 1–I usually tell my friends about category).
6. Overall, in my discussions with friends and neighbors about category, I am (7–often used as a source of advice to 1–not used as a source of advice).

References

Anderson, E. W. 1998. Customer satisfaction and word of mouth. *J. Service Res.* **1**(1) 5–17.

Anderson, E. W., M. W. Sullivan. 1993. The antecedents and consequences of customer satisfaction for firms. *Marketing Sci.* **12**(2) 125–143.

Arndt, J. 1967. Role of product-related conversations in the diffusion of a new product. *J. Marketing Res.* **4**(August) 291–295.

Bearden, W., M. Etzel. 1982. Reference group influence on product and brand purchase decisions. *J. Consumer Res.* **9** 183–194.

Bell, D. R., S. Song. 2004. Social contagion and trial on the Internet: Evidence from online grocery retailing. Wharton School Marketing Department Paper, University of Pennsylvania, Philadelphia.

Biyalogorsky, E., E. Gerstner, B. Libai. 2001. Customer referral management: Optimal reward programs. *Marketing Sci.* **20**(1) 82–95.

Bloch, P. H., M. L. Richins. 1983. A theoretical model for the study of product importance perceptions. *J. Marketing* **47**(3) 69–81.

Bolton, R. N., J. H. Drew. 1992. Mitigating the effect of service encounters. *Marketing Lett.* **3**(1) 57–70.

Bowman, D., D. Narayandas. 2001. Managing customer-initiated contacts with manufacturers: The impact on share of category requirements and word-of-mouth behavior. *J. Marketing Res.* **38**(3) 291–297.

Cameron, A. C., P. K. Trivedi. 1998. *Regression Analysis of Count Data*. Cambridge University Press, Cambridge, UK.

Chaudhuri, A., M. B. Holbrook. 2001. The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. *J. Marketing* **65**(2) 81–93.

Chevalier, J. A., D. Mayzlin. 2006. The effect of word of mouth on sales: Online book reviews. *J. Marketing Res.* **43**(3) 345–354.

Cialdini, R., B. Sagarin. 2005. Principles of interpersonal influence. T. Brock, M. Green, eds. *Persuasion: Psychological Insights and Perspectives*, 2nd ed. Sage Publications, Thousand Oaks, CA, 143–169.

Coleman, J. S., E. Katz, H. Menzel. 1966. *Medical Innovation: A Diffusion Study*. Bobbs-Merrill, Indianapolis.

Engel, J. E., R. D. Blackwell, R. J. Kegerreis. 1969. How information is used to adopt an innovation. *J. Advertising Res.* **9**(4) 3–8.

Foster, A., M. Rosenzweig. 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. *J. Political Econom.* **103**(6) 1176–1210.

Friestad, M., P. Wright. 1994. The persuasion knowledge model: How people cope with persuasion attempts. *J. Consumer Res.* **21**(1) 1–31.

Garber, T., J. Goldenberg, B. Libai, E. Muller. 2004. From density to destiny: Using spatial dimension of sales data for early prediction of new product success. *Marketing Sci.* **23**(3) 419–428.

Godes, D. B., D. Mayzlin. 2004. Using online conversation to study word-of-mouth communication. *Marketing Sci.* **23**(4) 545–560.

Godes, D., D. Mayzlin, Y. Chen, S. Das, C. Dellarocas, B. Pfeiffer, B. Libai, S. Sen, M. Shi, P. Verlegh. 2005. The firm's management of social interactions. *Marketing Lett.* **16**(3/4) 415–428.

Godes, D., E. Ofek. 2004. *Case Study: Hasbro Games—POX*. Harvard Business School Publishing, Boston.

Goldenberg, J., B. Libai, E. Muller. 2001. Talk of the network: A complex systems look at the underlying process of word-of-mouth. *Marketing Lett.* **12**(3) 211–223.

Granovetter, M. 1973. The strength of weak ties. *Amer. J. Sociol.* **78**(6) 1360–1380.

Gupta, S., C. F. Mela, J. M. Vidal-Sanz. 2006a. The value of a "free" customer. HBS Working Paper 07-035, Harvard Business School, Boston.

Gupta, S., B. Hardie, W. Kahn, V. Kumar, N. Lin, N. Ravishanker, S. Sriram. 2006b. What is the true value of a lost customer? *J. Service Res.* **9**(2) 139–155.

Hartmann, W. R., V. B. Viard. 2008. Do frequency reward programs create switching costs? A dynamic structural analysis of demand in a reward program. *Quant. Marketing Econom.* **6**(2) 109–137.

Hogan, J. E., K. N. Lemon, B. Libai. 2003. What is the true value of a lost customer? *J. Service Res.* **5**(3) 196–208.

Holmes, J. H., J. D. Lett. 1977. Product sampling and word of mouth. *J. Advertising Res.* **17**(5) 35–40.

Jacoby, J., W. D. Hoyer. 1981. What if opinion leaders didn't know more? A question of nomological validity. K. B. Monroe, ed. *Advances in Consumer Research*, Vol. 8. Association for Consumer Research, Ann Arbor, MI, 299–303.

Jacoby, J., D. B. Kyner. 1973. Brand loyalty vs. repeat purchasing behavior. *J. Marketing Res.* **10**(1) 1–9.

Kardes, F. 2002. *Consumer Behavior and Managerial Decision Making*, 2nd ed. Prentice Hall, Upper Saddle River, NJ.

Katz, E., P. F. Lazarsfeld. 1955. *Personal Influence*. Free Press, Glencoe, IL.

Keller, E., J. Berry. 2003. *The Influentials*. Free Press, New York.

Keller, K. L., D. R. Lehmann. 2006. Brands and branding: Research findings and future priorities. *Marketing Sci.* **25**(6) 740–759.

Khermouch, G., J. Green. 2001. Buzz marketing: Suddenly this stealth strategy is hot—But it's still fraught with risk. *Bus. Week* (July 30) 50.

King, C. W., J. O. Summers. 1970. Overlap of opinion leadership across consumer product categories. *J. Marketing Res.* **7**(1) 43–50.

Krishnamurthi, L., S. P. Raj. 1991. An empirical analysis of the relationship between loyalty and consumer price elasticity. *Marketing Sci.* **10**(2) 172–183.

Kruglanski, A. W., O. Mayseless. 1990. Classic and current social comparison research: Expanding the perspective. *Psych. Bull.* **108**(2) 195–208.

Manchanda, P., Y. Xie, N. Youn. 2008. The role of targeted communication and contagion in new product adoption. *Marketing Sci.* **27**(6) 961–976.

Mayzlin, D. 2006. Promotional chat on the Internet. *Marketing Sci.* **25**(2) 155–163.

Mazen, R., H. Leventhal. 1972. The influence of communicator-recipient similarity upon the beliefs and behavior of pregnant women. *J. Experiment. Soc. Psych.* **8** 289–302.

McConnell, B., J. Huba. 2003. *Creating Customer Evangelists*. Dearborn Trade Publishing, Chicago.

O'Malley, G. 2005. NBC goes viral in effort to win with "Biggest Loser." *MediaPost* (September 8), http://publications.mediapost.com.

Neff, J. 2006. P&G provides product launchpad, a buzz network of moms. *Advertising Age* (March 20), http://adage.com.

Neslin, S. A., C. Henderson, J. Quelch. 1985. Consumer promotions and the acceleration of product purchases. *Marketing Sci.* **4**(2) 147–165.

Petty, R. E., J. T. Cacioppo, A. J. Strathman, J. R. Priester. 2005. To think or not to think. T. Brock, M. Green, eds. *Persuasion: Psychological Insights and Perspectives*, 2nd ed. Sage Publications, Thousand Oaks, CA, 81–116.

Reichheld, F. F., W. E. Sasser. 1990. Zero defections: Quality comes to services. *Harvard Bus. Rev.* **68**(5) 105–111.

Reingen, P., B. Foster, J. J. Brown, S. Seidman. 1984. Brand congruence in interpersonal relations: A social network analysis. *J. Consumer Res.* **11**(3) 771–783.

Rogers, E. M. 1993. *Diffusion of Innovations*, 4th ed. Free Press, New York.

Rust, R. T., P. C. Verhoef. 2005. Optimizing the marketing interventions mix in intermediate-term CRM. *Marketing Sci.* **24**(3) 477–489.

Rust, R. T., T. S. Chung. 2006. Marketing models of service and relationships. *Marketing Sci.* **25**(6) 560–580.

Swan, J. E., R. L. Oliver. 1989. Postpurchase communications by consumers. *J. Retailing* **65**(4) 516–553.

Van den Bulte, C., Y. V. Joshi. 2007. New product diffusion with influentials and imitators. *Marketing Sci.* **26**(3) 400–421.

Van den Bulte, C., G. Lilien. 2001. *Medical Innovation* revisited: Social contagion versus marketing effort. *Amer. J. Sociol.* **106**(5) 1409–1435.

Van den Bulte, C., G. Lilien. 2003. Two-stage partial observability models of innovation adoption. ISBM Report 15-2001, Institute for the Study of Business Markets, The Pennsylvania State University, University Park.

Verlegh, P. W. J., C. Verkerk, M. A. Tuk, A. Smidts. 2004. Customers or sellers? The role of persuasion knowledge in customer referral. *Adv. Consumer Res.* **31** 304–305.

Walker, R. 2004. The hidden (in plain sight) persuaders. *New York Times* (December 5), http://www.nytimes.com/2004/12/05/magazine/05BUZZ.html.