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Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site

The authors study the effect of word-of-mouth (WOM) marketing on member growth at an Internet social networking site and compare it with traditional marketing vehicles. Because social network sites record the electronic invitations from existing members, outbound WOM can be precisely tracked. Along with traditional marketing, WOM can then be linked to the number of new members subsequently joining the site (sign-ups). Because of the endogeneity among WOM, new sign-ups, and traditional marketing activity, the authors employ a vector autoregressive (VAR) modeling approach. Estimates from the VAR model show that WOM referrals have substantially longer carryover effects than traditional marketing actions and produce substantially higher response elasticities. Based on revenue from advertising impressions served to a new member, the monetary value of a WOM referral can be calculated; this yields an upper-bound estimate for the financial incentives the firm might offer to stimulate WOM.

Keywords: word-of-mouth marketing, Internet, social networks, vector autoregression

Word-of-mouth (WOM) marketing has recently attracted a great deal of attention among practitioners. For example, several books tout WOM as a viable alternative to traditional marketing communication tools. One calls it the world's most effective, yet least understood marketing strategy (Misner 1999). Marketers are particularly interested in better understanding WOM because traditional forms of communication appear to be losing effectiveness (Nail 2005). For example, one survey shows that consumer attitudes toward advertising plummeted between September 2002 and June 2004. Nail (2005) reports that 40% fewer people agree that advertisements are a good way to learn about new products, 59% fewer people report that they buy products because of their advertisements, and 49% fewer people find that advertisements are entertaining.

Word-of-mouth communication strategies are appealing because they combine the prospect of overcoming consumer resistance with significantly lower costs and fast delivery—especially through technology, such as the Internet. Unfortunately, empirical evidence is currently scant regarding the relative effectiveness of WOM marketing in increasing firm performance over time. This raises the need to study how firms can measure the effects of WOM communications and how WOM compares with other forms of marketing communication.

Word-of-mouth marketing is a particularly prominent feature on the Internet. The Internet provides numerous venues for consumers to share their views, preferences, or experiences with others, as well as opportunities for firms to take advantage of WOM marketing. As one commentator stated, "Instead of tossing away millions of dollars on Superbowl advertisements, fledgling dot-com companies are trying to catch attention through much cheaper marketing strategies such as blogging and [WOM] campaigns" (Whitman 2006, p. B3A). Thus, it is important to understand whether WOM is truly effective and, if so, how its impact compares with traditional marketing activities.

One of the fastest-growing arenas of the World Wide Web is the space of so-called social networking sites. A social networking site is typically initiated by a small group of founders who send out invitations to join the site to the members of their own personal networks. In turn, new members send invitations to their networks, and so on. Thus, invitations (i.e., WOM referrals) have been the foremost driving force for sites to acquire new members. As social networking sites mature, they may begin to increase their use of traditional marketing tools. Therefore, management may begin to question the relative effectiveness of WOM at this stage.

The objective of this research is to develop and estimate a model that captures the dynamic relationships among new member acquisition, WOM referrals, and traditional marketing activities. In doing so, we offer several contributions. First, we are among the first to link observed WOM directly to new customer acquisition. Second, we show how to

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incorporate both the direct effects and the indirect effects of WOM and traditional marketing actions (e.g., a marketing action increases WOM activity, which in turn increases new member acquisition). We empirically demonstrate, for our data set, the endogeneity among new member sign-ups and these marketing variables. This highlights the need to account for these indirect effects to avoid biased estimates for both WOM and traditional marketing effects. Third, we quantify and contrast the immediate and long-term elasticities of WOM and traditional marketing actions. In particular, we document strong carryover effects for WOM in our data. Finally, we attach an estimated monetary value to each WOM referral, providing an upper bound to the financial incentive management might consider offering for WOM referrals. Indeed, the practice of seeding or stimulating WOM has grown rapidly, but quantifying the effectiveness of this activity remains difficult (e.g., Godes and Mayzlin 2004).

We organize the remainder of this article as follows: We begin by summarizing previous research to help put our contributions in perspective. We then describe our modeling approach. Next, we present our empirical analysis of the data from a collaborating Internet social networking site and offer implications for theory and managers. In particular, we find that WOM referrals strongly affect new customer acquisitions and have significantly longer carryover than traditional forms of marketing used by the firm (21 days versus 3 to 7 days). We estimate a long-term elasticity for WOM of .53—approximately 20–30 times higher than the elasticities for traditional marketing.

Research Background

To help put the intended contribution of this study in context, we briefly review previous empirical research on the effectiveness of WOM marketing. In Table 1, we present a comparison chart of selected prior work. As the table shows, researchers have used a variety of means to capture, infer, or measure WOM. The table also outlines findings for the effect of WOM on customer acquisition, comparisons with traditional marketing, and incorporation of indirect effects.

The earliest study on the effectiveness of WOM is survey based (Katz and Lazarsfeld 1955) and was followed by more than 70 marketing studies, most of them also inferring WOM from self-reports in surveys (Godes and Mayzlin 2004; Money, Gilly, and Graham 1998). Researchers have examined the conditions under which consumers are likely to rely on others' opinions to make a purchase decision, the motivations for different people to spread the word about a product, and the variation in strength of people's influence on their peers in WOM communications. Moreover, customers who self-report being acquired through WOM add more long-term value to the firm than customers acquired through traditional marketing channels (Villanueva, Yoo, and Hanssens 2008).

Social contagion models (e.g., Coleman et al. 1966) offer an alternative perspective, typically inferring WOM/network effects from adoption behavior over time. Although a social contagion interpretation of diffusion patterns is intuitively appealing, recent studies have pointed out that such inferences can be due to misattribution. For example, when Van den Bulte and Lilien (2001) reestimated Coleman and colleagues' (1966) social contagion model for physician adoption of tetracycline, they found that the contagion effects disappeared when marketing actions were included in the model. This raises the question whether WOM effects would have been significant in the model had there been data available on the actual transmission of information from one physician to another.

Both of these research approaches do not observe actual WOM but infer it from self-reports or adoption. Examining WOM on the Internet can help address this limitation by offering an easy way to track online interactions. Godes and Mayzlin (2004) suggest that online conversations (e.g., Usenet posts) can offer an easy and cost-effective way to measure WOM. In an application to new television shows, they link the volume and dispersion of conversations across different Usenet groups to offline show ratings. Chevalier and Mayzlin (2006) use book reviews posted by customers at Amazon.com and Barnesandnoble.com online stores as a proxy for WOM. They find that though most reviews were positive, an improvement in a book's reviews led to an increase in relative sales at the site, and the impact of a negative review was greater than the impact of a positive one. In contrast, Liu (2006) shows that both negative and positive WOM increase performance (box office revenue).

Although the foregoing three studies observe the posting of reviews (i.e., sending WOM), they do not directly observe the reception of WOM. In contrast, De Bruyn and Lilien (2008) observe the reactions of 1100 recipients after they received an unsolicited e-mail invitation from one of their acquaintances to participate in a survey. They find that the characteristics of the social tie influenced recipients' behaviors but had varied effects at different stages of the decision-making process. They also report that tie strength exclusively facilitated awareness, perceptual affinity triggered recipients' interest, and demographic similarity had a negative influence on each stage of the decision-making process. However, this study does not compare the effectiveness of WOM with that of traditional marketing actions, nor does it quantify the monetary value of WOM to the company.

The current article differs from these studies in both research objective and application. A key research objective in this study is to compare the effects of observed WOM referrals with those of traditional marketing efforts. Quantifying the full effects of WOM referrals and marketing requires us (1) to account for the potential endogeneity among these communication mechanisms and (2) to account for their potential permanent effects on customer acquisition. First, WOM may be endogenous because it not only influences new customer acquisition but also is itself affected by the number of new customers. Likewise, traditional marketing activities may stimulate WOM; they should be credited for this indirect effect and the possible direct effect on customer acquisition. Second, all these communication mechanisms may have permanent effects on customer acquisition. For example, WOM may be passed along beyond its originally intended audience and

TABLE 1
Comparison of Empirical Studies on the Effectiveness of WOM

	WOM Inference	Effect of WOM on Customer Acquisition	Comparison with Traditional Marketing	Indirect Effects of WOM and/or Traditional Marketing
Initial (Katz and Lazarsfeld 1955) and most studies	Self-report from surveys	Inferred from self-reports on relative influence	WOM two times more effective than radio advertisements, four times more than personal selling, seven times more than print advertisements	Not analyzed
Customer lifetime value (Villanueva, Yoo, and Hanssens 2008)	Inferred from new customer's self-report	Not analyzed	Customers acquired through WOM add two times the lifetime value of customers acquired through traditional marketing	Customers acquired through WOM spread more WOM and bring in twice as many new customers
Social contagion (Coleman, Katz, and Menzel 1966; Van den Bulte and Lilien 2001)	Inferred from adoption	Difficult to attribute observed contagion to WOM versus traditional marketing	Contagion effects disappear when traditional marketing effects are included in the model	Not analyzed
Determinants of WOM transmissions (Stephen and Lehmann 2008)	Directly: person's decision to transmit WOM in experimental setting	Expected responsiveness of WOM recipient drives transmitter's decision to pass WOM	None	Not analyzed
Valence of online WOM (Chevalier and Mayzlin 2006; Liu 2006)	Inferred from Web site posts and reviews	Higher number of reviews leads to higher relative sales	None	Not analyzed
Impact of social ties on WOM effect (De Bruyn and Lilien 2008)	Directly: though e-mails sent	Social tie effects depend on stage of decision making	None	Not analyzed
This article	Directly: through referrals sent	Quantify direct and indirect effects of WOM and marketing	Compare immediate and carryover effects of WOM and traditional marketing	Demonstrate indirect effects and quantify total monetary value of WOM activity

thus increase the site's potential to recruit sign-ups in the future.[1] Network externalities can also imply that sign-up gains today may translate into higher sign-up gains tomorrow, even in the absence of marketing actions.

Internet Social Networking Sites

In the past few years, social networking sites have become extremely popular on the Internet. According to comScore Media Metrix (2006), every second Internet user in the United States has visited at least one of the top 15 social networking sites. Approximately 50 social networking Web sites each have more than one million registered users, and several dozen smaller, though significant, sites also exist (e.g., Wikipedia 2008). Compete.com (2008), a Web traffic analysis company, reported that the largest online social networking site (as of November 2008) was MySpace, with 56 million unique visitors per month, closely followed by Facebook, with 49 million unique visitors.

Typical social networking sites allow a user to build and maintain a network of friends for social or professional interaction. The core of a social networking site consists of personalized user profiles. Individual profiles are usually a combination of users' images (or avatars); lists of interests and music, book, and movie preferences; and links to affiliated profiles ("friends"). Different sites impose different levels of privacy in terms of what information is revealed

[1]We thank an anonymous reviewer for this insight.

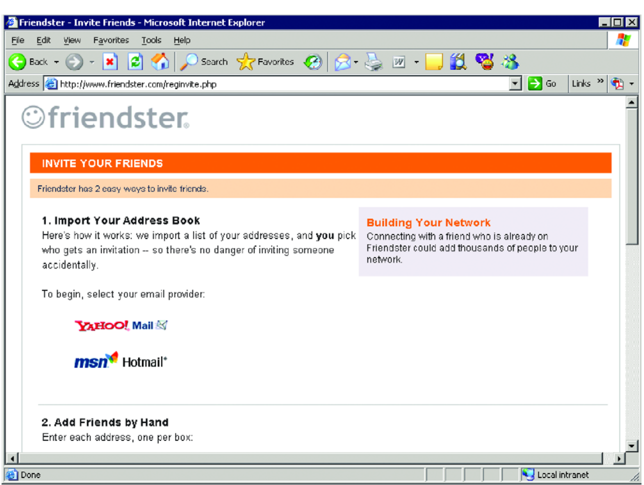
through profile pages to nonaffiliated visitors and how far "strangers" versus "friends" can traverse through the network of a profile's friends. Profile holders acquire new friends by browsing and searching through the site and sending requests to be added as a friend. Other forms of relationship formation also exist.

In contrast to other Internet businesses, online communities rely on user-generated content to retain users. Thus, a community member has a direct benefit from bringing in more friends (e.g., by participating in the referral program) because each new member creates new content, which is likely to be of value to the inviting (referring) party. Typically, sites facilitate referrals by offering users a convenient interface for sending invitations to nonmembers to join. Figure 1 shows how a popular social networking site, Friendster, implements the referral process.

The social network setting offers an appealing context in which to study WOM. The sites provide easy-to-use tools for current users to invite others to join the network. The electronic recording of these outbound referrals opens a new window into the effects of WOM, giving researchers an unobtrusive trace of this often difficult-to-study activity. When combined with data that also track new member sign-ups, it becomes possible to model the dynamic relationship between this form of WOM and the addition of new members to the social networking site. In a real sense, these members are also "customers" of the social networking site insofar as their exposure to advertising while using the site produces revenue for the firm.

Our empirical application to an Internet social networking site provides a set of substantive findings based on actual consumer WOM activity. In previously analyzed settings, such as movies and television shows, the Internet gives a partial view of interpersonal communication. For some product categories though, the vast majority of WOM may transfer online. For online communities, the electronic form of "spreading the word" is the most natural one. This

FIGURE 1
Referrals Process at Friendster.com



leads us to suggest that online WOM is a good proxy for overall WOM in our Internet social network setting.

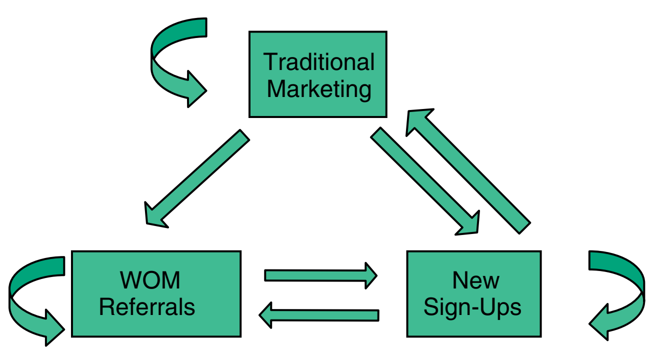
Modeling Approach

In this section, we describe our approach to modeling the effects of WOM and traditional marketing on new member sign-ups. First, we test for the potential endogeneity among WOM, marketing, and new customer acquisition and for the potential permanent effects of these communication mechanisms. Second, we specify a vector autoregressive (VAR) model that accounts for endogeneity and the dynamic response and interactions between marketing variables and outcomes (Dekimpe and Hanssens 1999). Next, we compare the in-sample and out-of-sample fit of the VAR model with several alternative models. Finally, we estimate the short-term and long-term responses of sign-ups to WOM and traditional marketing actions and compute the corresponding elasticities. Although we describe our approach in the context of WOM referrals and social networking, the procedure should be applicable on a more general basis (e.g., when data on new customers, tracked WOM, and other marketing activity are available over time).

The first step in our approach is to test for the presence of endogeneity among new sign-ups (our measure of customer acquisition), event marketing (directly paid for by the social networking site), media appearances (induced by public relations), and WOM referrals. As Figure 2 shows, we anticipate that WOM referrals lead to new sign-ups and (following the reverse arrow) that new sign-ups lead to more WOM referrals and, thus, indirectly to more new sign-ups. We anticipate a similar pattern of causality for new sign-ups and traditional marketing activity. It is also likely that traditional marketing will stimulate WOM referrals, leading to another indirect effect on new sign-ups. We also include lagged effects of traditional marketing, new sign-ups, and WOM referrals in the model (as the curved arrows indicate).

The links represented in Figure 2 can be tested by investigating which variables Granger-cause other variables (Granger 1969; Hanssens, Parsons, and Schultz 2001). In essence, Granger causality implies that knowing the history of a variable X helps explain a variable Y, beyond Y's own

FIGURE 2
Modeling Framework



history. This "temporal causality" is the closest proxy for causality that can be gained from studying the time series of the variables (i.e., in the absence of manipulating causality in controlled experiments). We perform a series of Granger-causality tests on each pair of key variables.[2] If sign-ups indeed Granger-cause (some of) the marketing variables, we need to capture the complex interactions of Figure 2 in a full dynamic system.

Next, we test for the potential of permanent effects of the communication mechanisms on new sign-ups. If any of these mechanisms expand the intended site audience or induce network externalities, sign-up gains today imply higher sign-up gains tomorrow. In this case, the time series for sign-ups would be classified as "evolving." The opposite classification, that of "stationary," implies that sign-ups have a fixed mean and that changes (including those caused by marketing actions) do not have a permanent impact (e.g., Dekimpe and Hanssens 1995, 1999). (The Appendix provides details on testing for evolution versus stationarity of new sign-ups.)

Tests for both endogeneity and evolution enable us to specify the VAR model in Equation 1. In this model, new sign-ups and marketing actions are endogenous—that is, they are explained by their own past and the past of the other endogenous variables (Dekimpe and Hanssens 1999). Specifically, the vector of endogenous variables—sign-ups (Y), WOM referrals (X), media appearances (M), and promotional events (E)—is related to its own past, which allows for complex dynamic interactions among these variables. The vectors of exogenous variables include for each endogenous variable (1) an intercept, C; (2) a deterministic-trend variable, T, to capture the impact of omitted, gradually changing variables; (3) indicators for days of the week, D; and (4) seasonal (e.g., holidays) dummy variables, H (Pauwels and Dans 2001). Instantaneous effects are captured by the variance–covariance matrix of the residuals, Σ. The VAR specification is given by

$$(1)\quad \begin{bmatrix} Y_t \\ X_t \\ M_t \\ E_t \end{bmatrix} = \begin{bmatrix} C_Y \\ C_X \\ C_M \\ C_E \end{bmatrix} + \begin{bmatrix} \delta_Y \\ \delta_X \\ \delta_M \\ \delta_E \end{bmatrix} \times T + \begin{bmatrix} \theta_Y \\ \theta_X \\ \theta_M \\ \theta_E \end{bmatrix} \times H + D \begin{bmatrix} \gamma_Y \\ \gamma_X \\ \gamma_M \\ \gamma_E \end{bmatrix}$$

$$+ \sum_{j=1}^{J} \begin{bmatrix} \phi_{11}^j & \phi_{12}^j & \phi_{13}^j & \phi_{14}^j \\ \phi_{21}^j & \phi_{22}^j & \phi_{23}^j & \phi_{24}^j \\ \phi_{31}^j & \phi_{32}^j & \phi_{33}^j & \phi_{34}^j \\ \phi_{41}^j & \phi_{42}^j & \phi_{43}^j & \phi_{44}^j \end{bmatrix} \begin{bmatrix} Y_{t-j} \\ X_{t-j} \\ M_{t-j} \\ E_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Y,t} \\ \varepsilon_{X,t} \\ \varepsilon_{M,t} \\ \varepsilon_{E,t} \end{bmatrix},$$

where t indexes days, J equals the number of lags included (to be determined on the basis of the Akaike information criterion), D is the vector of day-of-week dummies, and ε_t are white-noise disturbances distributed as N(0, Σ). The parameters δ, θ, γ, and ϕ are to be estimated. Because VAR model parameters are not interpretable on their own (Sims 1980), effect sizes and significance are determined through the analysis of impulse response functions (IRFs) and elasticities computed on the basis of the model (for details, see the Appendix).

The last step of the approach uses the model to estimate the short-term and long-term elasticities of customer acquisition to WOM and traditional marketing actions. From these results, several managerial implications can be drawn. We also show how the model can be used to estimate the potential monetary value of each WOM referral (described further in the Appendix).

Empirical Analysis

Data Description

We applied our model to data from one of the major social networking sites, which prefers to remain anonymous. The data set contains 36 weeks of the daily number of sign-ups and referrals (provided to us by the company) along with marketing events and media activity (obtained from third-party sources). The data cover the period in 2005 from February 1 to October 16. Table 2 provides descriptive statistics for the variables.

During the observation period, the daily sign-ups and WOM referrals showed a positive trend. We observed somewhat lower activity in referrals over the summer season (June 20–September 5 [Labor Day, as observed in the United States]). Over the 36 weeks, the company organized or cosponsored 101 promotion events. On some days, multiple events occurred in different locations. Overall, 86 days in the observation period had some promotion event activity. Finally, we identified 236 appearances (on 127 days) of the company name in the media. We considered 102 different sources, both electronic and traditional media, as provided by Factiva News and Business Information Service (www.factiva.com). We did not use the content of these publications, which makes our measure of media activity somewhat coarse. More generally, it could be important to account for the valence of the message (e.g., Godes and Mayzlin [2004] report for television shows). Given the relatively young age of the company, we had no reason to

TABLE 2
Descriptive Statistics (Daily Data)

	M	Mdn	Maximum	Minimum	SD
Sign-ups	11.36	11.30	11.89	10.86	.29
WOM referrals[a]	11.37	11.42	12.09	10.53	.38
Media	.92	0	8	0	1.34
Events	.39	0	4	0	.64

[a]The figures reflect a linear transformation of the original daily data to preserve the anonymity of the collaborating site. Actual data were used in the econometric analyses.

[2]A wrong choice for the number of lags in the test may erroneously conclude the absence of Granger causality (e.g., Hanssens 1980). Because we are applying these tests to investigate the need for modeling a full dynamic system, we are not interested in whether variable X causes variable Y at a specific lag but rather in whether we can rule out that X Granger-causes Y at any lag. Therefore, we run the causality tests for lags up to 20 and report the results for the lag that has the highest significance for Granger causality.

believe that a significant share of the media reports would have a negative tone. We removed a few negative "suspects" from the sample, as judged by the title of the publication, but found no significant impact on the results. In summary, the number of media appearances is a useful measure for our research purpose.

Test Results for Evolution and Endogeneity

We begin our empirical analysis by first testing for stationarity versus evolution in each time series. The unit-root tests indicated trend stationarity in all series (i.e., all series appeared to be stationary after we controlled for a deterministic trend). This indicates that model estimations can be performed with all variables in levels (as we depict in Equation 1).

To investigate whether endogeneity is present among the variables, we conducted Granger-causality tests. We summarize the results in Table 3. Each cell gives the minimum *p*-value obtained from the causality tests as conducted from 1 lag to 20 lags.

The results clearly show that endogeneity is present among the variables in our data. As we expected, Granger causality is detected for WOM referrals, media, and events on sign-ups (the direct effects). In addition, Granger causality is found for many of the other pairings. For example, sign-ups Granger-cause WOM referrals (the interdependent effect we noted previously), events (indicating management performance feedback; see Dekimpe and Hanssens 1999), and media (indicating that spikes in sign-ups may receive media attention). Moreover, events Granger-cause media (indicating that media covers events), and media Granger-cause events (indicating that management may try to time events to match pending media coverage). However, WOM referrals do not Granger-cause events or media appearances (because the media do not observe referrals directly), and media appearances do not Granger-cause WOM. In summary, the results from the Granger-causality tests indicate the need to consider the full dynamic system, as in a VAR model, and to account for the indirect effects of marketing actions.

Model Estimation

We estimated the VAR model of Equation 1 with two lags (the optimal lag length selected by the Akaike information criterion) and found good model fit (e.g., $R^2 = .89$). We also assessed the significance of including WOM and the traditional marketing variables for events and media in the model at the same time. This is intended to address Van den Bulte and Lilien's (2001) concern about the significance of WOM when marketing variables are incorporated. In particular, we estimated two VAR models nested in Equation 1. In the first, we estimated the model without the WOM variable. In the second, we estimated the model without events and media. In both cases, the full model provided superior fit in-sample and out-of-sample based on both root mean square error (RMSE) and mean absolute deviation (MAD). Thus, WOM and traditional marketing remain significant contributors to model fit.

To illustrate the ability of the VAR system model to represent the data, we plot predicted versus actual values of daily sign-ups and display this in Figure 3. The predicted values (labeled VAR) closely track the actual number of sign-ups.

TABLE 3
Results of the Granger Causality Tests (Minimum *p*-Values Across 20 Lags)

Dependent Variable Is Granger-Caused by	Sign-Ups	WOM Referrals	Media	Events
Sign-ups	—	.02[a]	.00	.00
WOM referrals	.00	—	.22	.08
Media	.00	.58	—	.02
Events	.02	.00	.01	—

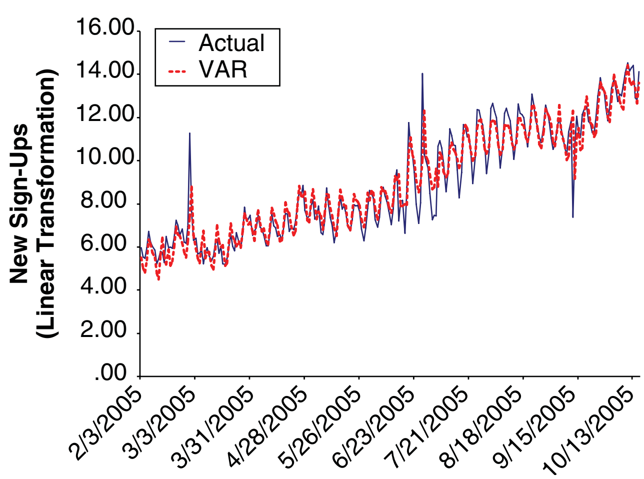
[a]WOM referrals are Granger-caused by sign-ups at the .02 significance level.

Short-Term and Long-Term Effects for WOM and Traditional Marketing Actions

To gauge the impact of WOM and the two traditional marketing variables on new sign-ups over time, we compute IRFs on the basis of the estimated VAR system parameters (for details, see the Appendix). The IRFs trace the incremental effect of a one-standard-deviation shock in WOM, events, and media on the future values of sign-ups. These enable us to examine the carryover effects of each activity on sign-ups while fully accounting for the indirect effects of these activities in a dynamic system. Figure 4 plots the three IRFs for the effect of WOM referrals, media, and events on new sign-ups over time.

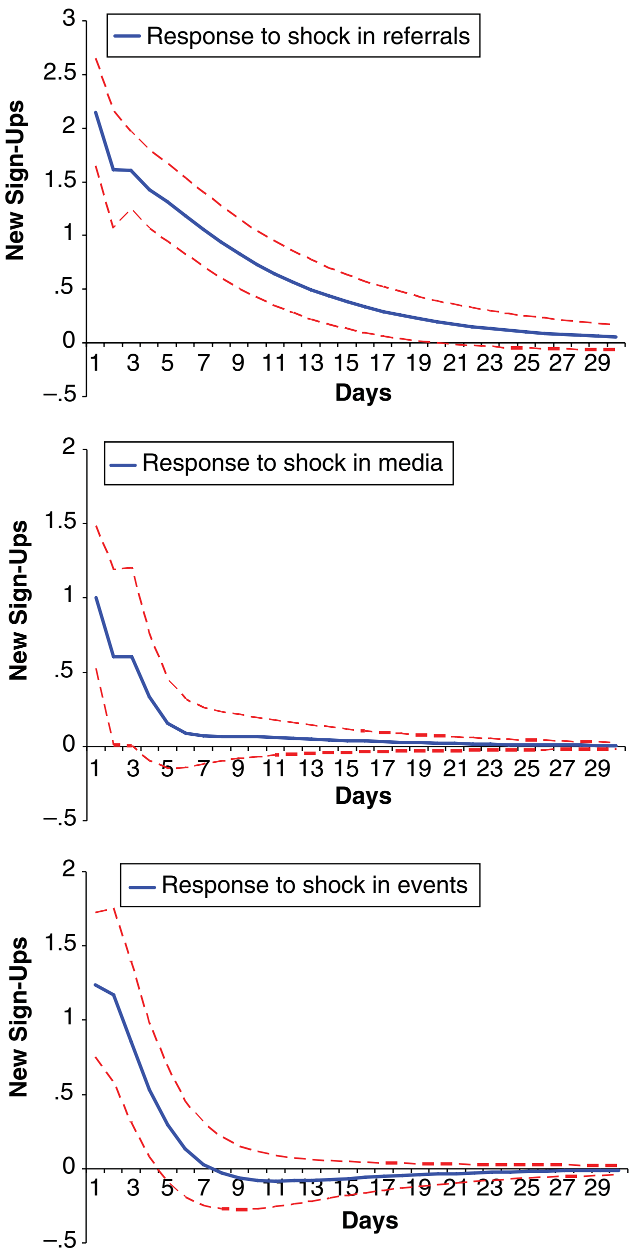
The top panel in Figure 4 shows that the WOM effect on sign-ups remains significantly different from zero for approximately three weeks. In contrast, the effects of media and events (the middle and bottom panels of Figure 4) lose significance within just a few days. Compared with traditional marketing activities, the WOM referrals induce both

FIGURE 3
Model Fit: Tracking Plot



Notes The y-axis values reflect a linear transformation used to disguise the identity of the source.

FIGURE 4
IRFs: Response of Sign-Ups to Shock in Referrals, Media, and Promotional Events



a larger short-term response and a substantially longer carryover effect. These results highlight the need for researchers to employ models that can also account for the longer-term effects of WOM marketing.

We also calculate several short-term elasticities and a long-term elasticity for WOM, events, and media. (Details on the computations appear in the Appendix.) Table 4 presents these estimated short- (one day, three days, and seven days) and long-term elasticities.

The immediate (one day) elasticity of WOM (.068) is 8.5 times higher than that of traditional marketing actions (.008). Moreover, this discrepancy grows over time. Indeed, the long-term elasticity indicates that WOM referrals are akin to the "gift that keeps on giving," especially compared with the performance of traditional marketing activities. Table 4 shows that the long-term elasticity of WOM referrals (.53) is approximately 20 times higher than the elasticity for marketing events (.53 versus .026) and 30 times higher than the elasticity for media appearances (.53 versus .017). The estimated WOM elasticity of .53 substantially exceeds the range of values for advertising elasticities reported in the literature (e.g., Hanssens, Parsons, and Schultz 2001). Thus, our empirical findings support the notion that WOM may be among the most effective marketing communication strategies.

TABLE 4
Short-Term Versus Long-Term Elasticity of Sign-Ups with Respect to WOM Referrals and Marketing Activities

	One Day	Three Days	Seven Days	Long-Term
WOM referrals	.068	.171	.330	.532
Media	.008	.017	.017	.017
Events	.008	.022	.026	.026

Comparison with Alternative Models

We compare the in-sample and out-of-sample fit of the VAR model with five alternative models (for details and specifications of each model [Equations A1–A5], see the Appendix).[3] First, an autoregressive (AR) model captures the immediate effects of marketing actions on sign-ups and the dynamic effect of past sign-ups on current sign-ups. Second, an autoregressive-distributed lag (ARDL) model adds dynamic effect of each communication mechanisms, without accounting for endogeneity and indirect effects among these mechanisms. Third, social contagion models (e.g., the Bass diffusion model) allow for several dynamic processes in the growth of online communities. We estimate versions both with and without marketing covariates. Finally, the effects of WOM and marketing variables could vary over the period of our data. Thus, a fifth model incorporates time-varying coefficients in a state-space specification. Table 5 compares the in-sample and out-of-sample fit of each model in terms of RMSE and MAD. Both in-sample and out-of-sample, the VAR model produces the lowest values for RMSE and MAD, indicating superior fit to the data.

Implications for Marketing Theory

Our investigation of WOM in an Internet social network setting offers several potential contributions for advancing the field's knowledge and understanding of WOM effects. First, the electronic tracking of WOM, along with new member sign-ups, enables us to provide a concrete and measurable link between observed WOM activity and customer acquisition. This bodes well for future efforts to quantify WOM effects and to incorporate them into the planning of marketing communication strategies.

[3]We thank the guest editor and reviewers for suggesting alternative models and the comparison tests.

TABLE 5
In-Sample and Out-of-Sample Performance for Alternative Models

		VAR	AR	ARDL	Base Bass	Bass with Covariates	Varying Coefficients
In-Sample	RMSE	.687	.731	.714	.784	.747	.692
	MAD	.457	.525	.521	.544	.529	.472
Out-of-Sample	RMSE	1.302	1.630	1.454	1.563	1.525	1.681
	MAD	1.051	1.384	1.182	1.217	1.207	1.427

A second set of theoretical implications comes from the dynamic performance of WOM marketing. Note that the strong carryover effects of WOM are the key factor driving its high long-term elasticity in our data. Notably, when estimated from standard regression models (the AR and ARDL models in the Appendix), the direct WOM elasticity is close to the average advertising elasticity of .10 to .20 (e.g., Hanssens, Parsons, and Schultz 2001). Accounting for carryover by the VAR system model produces a long-term elasticity that is several times higher. Our results provide further impetus for models of advertising to go beyond investigating the direct effects of advertising to incorporate a variety of potential indirect benefits, such as increasing retailer support (e.g., Reibstein and Farris 1995) and investor awareness (e.g., Joshi and Hanssens 2006).

Third, our findings highlight the importance of accounting for the indirect effects among WOM, traditional marketing actions, and performance. Conceptually, we illustrate this in Figure 2. Empirically, the Granger-causality tests indicated the presence of significant indirect and feedback effects in our data. Taken together with the superior fit provided by the VAR model compared with other approaches, the findings demonstrate the importance of handling the endogeneity that is likely to be present with WOM. Our framework and model also enable traditional marketing actions to be credited for their WOM-generating abilities. To the extent that modeling WOM alters estimated effect sizes for traditional marketing activities, the productivity of those activities could change, with potentially important implications for budgeting and resource allocation decisions.[4]

Though still a relatively new phenomenon, online social networking sites have begun to attract the attention of marketing scholars. For example, Ansari, Koenigsberg, and Stahl (2008) have developed an approach for modeling multiple relationships of different types among users of a social networking site. Dholakia, Bagozzi, and Pearo (2004) study two key group-level determinants of virtual community participation: group norms and social identity. Kozinets (2002) has developed a new approach to collecting and interpreting data obtained from consumers' discussions in online forums. Trusov, Bodapati, and Bucklin (2008) propose a model that enables managers to determine which users are likely to be influential and, therefore, important to the business for their role in attracting others to the site. Our research contributes to this emerging area of study by elucidating the role of WOM in the recruiting of new members and the growth of these social networks.

Managerial Implications

Managers should be able to make use of our research in several ways. These include obtaining improved metrics for both WOM and traditional marketing, testing changes in online WOM referral content, and evaluating the extent to which financial incentives can be used to stimulate WOM.

A practical benefit from applying the proposed model is likely to come from better measures of the effects of both WOM and traditional marketing. As we noted previously, the VAR model incorporates the potential endogeneity likely to be present with WOM, incorporates indirect effects among marketing variables and WOM, and allows each variable (WOM and traditional marketing) to have different—and potentially long-lasting—carryover effects. The general result is a potentially different estimate of the return on the firm's investments in traditional marketing.

To examine this, we compared the elasticity estimates for events and media obtained from the VAR model (Table 4) with those from the best-fitting standard regression (the ARDL model). The results from the standard regression model show neither events nor media registering significant short-term or long-term effects. Specifically, to three decimal places, we estimate the elasticities for events and media at .002 and .000, respectively. In the VAR model, however, these effects, though still relatively small, are larger and significant (see Table 4).

Managers can also use our approach to test changes to referral content. When an existing member wants to refer a friend to join the site (the outbound referrals we study), the member completes a preformatted message, which is then sent out by e-mail. At many social networking sites (including the major ones, such as Facebook and MySpace), members have relatively little control over the content and format of this invitation. Although there is room for a short text message, many of these are left blank. The upshot is that the firm is largely responsible for the appearance and content of the referral message. This provides the opportunity to test and refine the message. The firm could also

[4]Van den Bulte and Lilien (2001) raise the question whether WOM effects are significant after marketing actions are accounted for in a contagion model. To investigate this further, we estimated two additional VAR models. In the first, we dropped the traditional marketing variables, media and events, leaving all else unchanged. In the second, we dropped WOM. In both cases, we found no material change in the estimated elasticity values for WOM or media and events. Although the Granger-causality tests indicated that indirect effects were present, at least for our data, the ultimate elasticities we obtained did not substantially differ. Part of this may also be due to a greater robustness of VAR model estimates to omitted variables.

consider targeting different messages according to what is known about the referrer (e.g., demographics, usage history). Our modeling approach should be useful to managers in these and analogous settings as a means to gauge the effect of different content executions while controlling for other marketing activity. For example, this could be done by estimating the model on the data for different test periods or target samples.

Finally, our approach may help managers answer the question regarding the extent to which the firm should be prepared to invest in stimulating additional WOM. A growing practice in both offline and online markets is to offer financial incentives to existing customers to provide WOM referrals (e.g., Netflix has incentivized current subscribers to recruit new ones). Authors of several studies in the academic WOM literature have also suggested that companies should try to create WOM communication (e.g., Godes and Mayzlin 2004; Liu 2006; Rosen 2000). Important input for such a referral program would be the value WOM communication provides to the firm. This can be obtained from our data and model through simulation, and we describe one approach in the Appendix. Using some assumptions about current advertising rates, the simulation shows that each outbound referral sent out is worth approximately \$.75 per year in increased advertising revenue. By sending out ten referrals, each network member could bring in approximately \$7.50 of incremental ad revenue for the site.

An important caveat to the simulation is that it does not account for the possible difference between the quality of WOM that occurs naturally and WOM stimulated by the firm. When a company stimulates WOM activity, it is no longer "organic" WOM. Indeed, it could be called "fertilized" WOM. We do not know whether fertilized WOM would produce the same elasticity as the organic WOM observed in our data. If the paid nature of WOM activity is known to prospective members, fertilized WOM may be substantially less effective than organic WOM. In this respect, our monetary value calculations represent an upper bound of the money that could be generated by stimulating WOM.

Nonetheless, managers can use figures derived from this type of approach as an upper bound when contemplating the offer of financial incentives for WOM. For example, if the firm cannot effectively generate additional referrals at less than \$.75 each, it should not pursue firm-stimulated WOM programs.

Conclusion

The purpose of this study was to increase the understanding of the effects of WOM marketing by taking advantage of new, detailed tracking information made possible by the Internet. Using data from an online social networking site, we quantify the effect of WOM referrals, which are recorded electronically, on new member sign-ups to the site (i.e., customer acquisitions). We also compare the effect of WOM with traditional marketing activity and examine its carryover dynamics. This permits us to speak to the relative effectiveness of WOM both in the short run and in the long run.

We find that WOM referrals have a strong impact on new customer acquisition. The long-term elasticity of sign-ups with respect to WOM is estimated to be .53 (substantially larger than the average advertising elasticities reported in the literature). The elasticity for WOM is approximately 20 times higher than that for marketing events and 30 times that of media appearances. In addition, an important feature of the proposed modeling approach is the ability to handle the endogeneity and indirect effects among WOM, marketing activity, and customer acquisition.

Our work has several important implications for practicing managers. Our approach offers managers a tool to improve the metrics they use for assessing the effectiveness of traditional marketing when WOM effects are present. We also conducted a simulation analysis to illustrate the potential monetary implications from inducing additional WOM by offering financial incentives to existing customers.

We should also note the limitations to our research. Our data come from one large social networking site, cover a period of less than one year, and are at the aggregate level. Thus, data limitations prevent us from analyzing the effects of WOM for—and marketing actions by—competing sites. Though unfortunate, this is common to this type of company-specific data set. Because our data set tracks new sign-ups and WOM at the aggregate level, another limitation is that we are unable to model heterogeneity. Therefore, we do not address segmentation in WOM response or potential differences in wear-out or saturation effects at the individual level. In addition, site members attracted in different ways (i.e., through WOM, events, or media appearances) could differ in visit frequency and pages viewed, thus yielding different revenue benefits to the site (Villanueva, Yoo, and Hanssens 2008). Because we lacked such individual-level data, we could not make this distinction in our revenue calculations.

Another data-related limitation to our work is that the stationary nature of this company's sign-up series means that none of the changes to sign-ups (including those caused by WOM and other marketing actions) have a permanent impact. This is consistent with marketing effect findings for large, established brands across industries (e.g., Nijs et al. 2001; Srinivasan et al. 2004) but not with those for smaller brands (Slotegraaf and Pauwels 2008). In light of our description of how social networking sites start out (with a crucial mix of user-generated content and WOM of founders to friends), sign-up growth/evolution for small sites may be driven by network externalities (more user-generated content makes membership more valuable) and WOM transmission beyond the initial audience of the founders' friends. Moreover, smaller social networks may not have sufficient funding to engage in traditional marketing events and therefore must focus on cost-effective options, such as blogging and WOM campaigns (Whitman 2006). Thus, our estimates of WOM elasticities for an established site are likely to be conservative for smaller sites. In general, further research is needed to determine whether our substantive findings generalize to other companies and settings. Our results are consistent with the spirit of the results that East and colleagues (2005) report; in a review of 23 service categories, they find that WOM had greater reported impact on brand choice than advertising or personal search.

Finally, our model is in a reduced as opposed to structural form. This implies that the long-term impact calculations are subject to the assumption that the basic data-generating process does not change. This is appropriate for "innovation accounting"—that is, identifying and quantifying the effects of WOM and traditional marketing on sign-ups in the data sample (Franses 2005; Van Heerde, Dekimpe, and Putsis 2005). However, the modeling approach is not suited for revealing structural aspects of subscriber and company behavior.

In summary, our goal was to shed new light on the true effectiveness of WOM marketing—a vital but still poorly understood element of the marketing communications mix (Misner 1999). We do this by quantifying the dynamic performance effects of WOM in an Internet social network setting—a setting that offers researchers and managers a direct way to observe this phenomenon. Thus, we are among the first to link WOM to new customer acquisition. Our elasticity results add further evidence to the view that WOM communication is a critical factor for firms seeking to acquire new customers and that WOM can have larger and longer-lasting effects than traditional marketing activity.

Appendix

Testing for Evolution or Stationarity: Unit-Root Tests

We perform unit-root tests to determine whether each of the variables in our data set is stable (i.e., fluctuate temporarily around a fixed mean or trend) versus evolving (i.e., can deviate permanently from previous levels). We use both the augmented Dickey–Fuller test procedure that Enders (1995) recommends and Kwiatkowski and colleagues' (1992) test.

AR and ARDL Models

The AR specification in Equation A1 relates sign-ups to events, media, and WOM and controls for deterministic components, such as a base level (constant), a deterministic (time) trend, seasonality, and lags of the dependent variable (e.g., Box and Jenkins 1970):

$$\text{(A1)}\quad Y_t = \beta_1 X_t + \beta_2 M_t + \beta_3 E_t + C + \delta T + \sum_{i=1}^{6} \gamma_i d_i + \theta H_t + \sum_{j=1}^{J} \phi_j Y_{t-j} + \varepsilon_t.$$

Equation A1 includes the same variables as Equation 1, and J is the number of lags of the dependent variable (thus, the term "autoregressive") needed to ensure that the residuals ε_t are white-noise errors (no residual autocorrelation). We also check whether the interaction effects were significant, but we did not find any.

Equation A1 directly models only the immediate effects of marketing actions on sign-ups. Although this immediate effect may carry over to future periods through the AR parameters, the model assumes that such carryover does not depend on the marketing action that caused the immediate gain in sign-ups. To include dynamic effects specific to the marketing action, we can add lags of the marketing variables, obtaining the following ARDL model (e.g., Hanssens, Parsons, and Schultz 2001):[5]

$$\text{(A2)}\quad Y_t = \sum_{l=1}^{L} \beta_{1,l} X_{t-l} + \sum_{m=1}^{M} \beta_{2,m} M_{t-m} + \sum_{n=1}^{N} \beta_{3,n} E_{t-n} + C + \delta T + \sum_{i=1}^{6} \gamma_i d_i + \theta H_t + \sum_{j=1}^{J} \phi_j Y_{t-j} + \varepsilon_t,$$

where L, M, and N are the number of lags for the predictor variables WOM referrals, number of media appearances, and number of promotional events variables, respectively.

Social Contagion Model (Bass Diffusion Model)

Social contagion models (e.g., the Bass diffusion model) allow for several dynamic processes in the growth of online communities and have recently been applied to this setting (e.g., Firth, Lawrence, and Clouse 2006). An important issue is that stable and robust parameter estimates for the Bass model are obtained only if the data include the peak for the noncumulative adoption curve, which is difficult to assess a priori (Heeler and Hustad 1980; Srinivasan and Mason 1986). To address this problem, we assist the Bass model by using information about the number of site members observed in the time since the detailed original data were collected (specifically, two years later). We also ensure that the selected value for m (market capacity) provides the best possible model fit to the in-sample data. The Bass model and extended Bass model are both estimated with nonlinear least squares (e.g., Srinivasan and Mason 1986).

Our specification for the social contagion model follows the Bass diffusion model but also includes indicators for day of week and the summer holiday:

$$\text{(A3)}\quad Y_t = (m - Z_{t-1}) \times \left(p + q\frac{Z_{t-1}}{m}\right) + \sum_{i=1}^{6} \gamma_i d_i + \theta H_t,$$

where

t = day index,
m = number of eventual members (market capacity),
p = coefficient of innovation (external influence),
q = coefficient of imitation (internal influence [WOM]),
Y_t = number of sign-ups (new members),
Z_t = cumulative number of adopters (new members) at time t,
d_i = indicators for days of the week (using Friday as the benchmark),

[5]Our use of the term "dynamic" refers to the carryover effects that a change in one variable has on other variables over time. This differs from a model in which parameters themselves change over time, as we detail subsequently.

H = holiday indicator (summer vacation), and γ_{1-6} are parameters to be estimated.

We extend this social contagion model by augmenting Equation A3 with the marketing variables for media appearances and promotional events. This gives the following:

$$\text{(A4)} \qquad Y_t = (m - Z_{t-1}) \times \left(p + q\frac{Z_{t-1}}{m} + \beta_1 M_t + \beta_2 E_t \right) + \sum_{i=1}^{6} \gamma_i d_i + \theta H_t,$$

where

M_t = number of media appearances,
E_t = number of promotional events, and β_{1-2}, γ_{1-6}, and θ are parameters to be estimated.

Varying Coefficients Model

If the effects of WOM and marketing variables could vary over time, a logical alternative to the VAR model is a state-space specification with time-varying coefficients (e.g., Dekimpe et al. 2006; Kao and Allenby 2005). This gives where the coefficients for WOM and marketing variables become time varying:

$$\text{(A5)} \quad Y_t = \beta_1^t X_t + \beta_2^t M_t + \beta_3^t E_t + C + \delta T + \sum_{i=1}^{6} \gamma_i d_i + \theta H_t + \varepsilon_t,$$

where the coefficients for WOM and marketing variables become time varying and β_{1-3}^t, δ, γ_{1-6}, and θ are parameters to be estimated. We estimate this model using Kalman filter recursions (Harvey 1991).

In-Sample and Out-of-Sample Fit Analysis for Model Comparison

For the six models in Equations 1 and A1–A5, we perform an in-sample and out-of-sample fit analysis. We use the static forecasting technique for the out-of-sample analysis, treating both exogenous and any lagged endogenous variables as observed for every observation in the holdout. This "one-step-ahead" forecasting procedure is common in model comparison because it makes use of the same information set across competing models. We reserved the last two months of the data (61 observations) for a holdout test and reestimated all models on the first 197 daily observations (approximately 6.5 months). For each model, we computed two fit statistics—RMSE and MAD—for both the in-sample data (197 observations) and the holdout data (61 observations).

IRFs and Elasticities

Because it is infeasible to interpret estimated VAR model coefficients directly (Sims 1980), researchers use the estimated coefficients to calculate IRFs. The IRF simulates the over-time impact of a change (over its baseline) to one variable on the full dynamic system and represents the net result of all modeled actions and reactions (see Pauwels 2004). With regard to identification, we adopt the generalized IRF (i.e., simultaneous-shocking approach; Pesaran and Shin 1998). This uses information in the residual variance–covariance matrix of the VAR model instead of requiring the researcher to impose a causal ordering among the endogenous variables (Dekimpe and Hanssens 1999). We use IRFs to disentangle the short- and long-term effects of WOM and traditional marketing on sign-ups. Consistent with the VAR literature (Pesaran, Pierse, and Lee 1993; Sims and Zha 1999), we use $|t_{value}| < 1$ to assess whether each impulse–response value is significantly different from zero. This also follows the tradition of VAR-related research in marketing (Pauwels, Hanssens, and Siddarth 2002; Pauwels et al. 2004).

We translate IRFs into elasticities as follows: First, the IRF analysis yields the total change in number of sign-ups, ΔY, in response to a one-standard-deviation shock to, for example, WOM referrals. Second, using our data, we calculate the standard deviation for WOM referrals (σ_X) and mean values for sign-ups ($\bar{Y}$) and WOM referrals ($\bar{X}$). Finally, we calculate the arc elasticity:

$$\eta_{arc} = \frac{\Delta Y}{\sigma_X} \times \frac{\bar{X}}{\bar{Y}}.$$

Note that this is a standard elasticity formula, except that σ_X is substituted for ΔX. This follows because σ_X is the change in X used to generate the IRF.

Simulation to Obtain the Monetary Value of WOM

The simulation is based on the economics of online advertising standard to many social networking sites in which each customer acquisition translates into an expected number of future banner ad exposures. We use industry averages for cost per thousand impressions and number of impressions per user/day while making assumptions about a customer's projected lifetime with the firm. For cost per thousand impressions, we obtained price quotes from several social networking sites and concluded that approximately \$.40 is reasonable. For impressions, the average number of pages viewed on a community site by a unique visitor per month is approximately 130 (Nielsen/NetRatings 2005). Assuming that the average page carries two to three advertisements, we calculate that the average user contributes approximately \$.13 per month or approximately \$1.50 per year. From the IRF analysis, we know that ten WOM referrals bring in an estimated five new site members over the course of three weeks.[6] This suggests that each outbound referral is worth approximately \$.75 per year. By sending out ten referrals, each network member could bring in approximately \$7.50 to the firm. Practitioners should view these results with caution because the measures used may vary. In addition, other online advertising models, such as pay-per-click, pay-per-lead, and pay-per-sale could be analyzed by substituting appropriate conversion rates.

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[6]In our data set, the ratio of daily average number of sign-ups to the daily average number of WOM referrals is close to one (Table 2). Accordingly, the estimation of long-term marginal effect of WOM (.52) appears to be not significantly different from the estimation of WOM elasticity (.53). Additional details on the simulation and estimation of alternative models are available on request.

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