ESTIMATING THE DYNAMIC EFFECTS OF ONLINE WORD-OF-MOUTH ON MEMBER GROWTH OF A SOCIAL NETWORK SITE

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May 12, 2007

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ABSTRACT

The authors study the effects of word-of-mouth (WOM) marketing on member growth at an Internet social networking site. Because such sites track the electronic invitations sent out by existing members, outbound WOM may be precisely tallied daily and then linked to the number of new members joining the site (signups). To handle the potential endogeneity among WOM, new signups, and traditional marketing activity, the authors use a Vector Autoregression (VAR) modeling approach to quantify the short- and long-term effects of WOM referrals. First, Granger causality tests demonstrate the endogeneity among signups and WOM referrals. Second, word-of-mouth referrals have substantially longer carryover effects than traditional marketing actions. Specifically, the long-run elasticity of signups to WOM is estimated at close to 0.5 – about 2.5 times larger than the average advertising elasticities reported in the literature. The authors also report that the estimated WOM effect is about 20 times higher than the elasticity for marketing events, and 30 times larger than that of media appearances. Using the estimated Internet display advertising revenue produced by impressions served to a new member, the monetary value of a WOM referral is calculated, yielding an upper bound estimate for the financial incentives the firm might offer to stimulate word-of-mouth.

Keywords: Word-of-Mouth Marketing, Internet, Social Networks, Vector Autoregression Model

Introduction

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

Meanwhile, WOM marketing strategies are appealing because they combine the promise 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 word-of-mouth communications and how WOM compares to other forms of marketing communication.

WOM marketing is particularly prominent on the Internet. As one commentator stated, "Instead of tossing away millions of dollars on Superbowl ads, fledging dot-com companies are trying to catch attention through much cheaper marketing strategies such as blogging and word-of-mouth campaigns" (Whitman 2006). Now that many of these companies have "grown up" and venture capital is flowing back to their coffers (e.g., the Superbowl ads of Careerbuilder.com and GoDaddy.com), it is of broad interest to understand the effectiveness of word-of-mouth.

One of the fastest growing arenas of the World Wide Web is the space of so-called social networking sites (e.g., Friendster, Facebook, Xanga). These sites rely upon user-generated content to attract and retain visitors and obtain revenue primarily from the sale of online advertising. They also accumulate user information that may be valuable for targeted marketing purposes. The social network setting offers an attractive context to study word-of-mouth. The sites provide easy-to-use tools for current users to invite others to join the network and they track these referral activities. The electronic recording of outbound referrals opens a new window into the effects of WOM, giving researchers an unobtrusive trace of this hard-to-study activity. When combined with data that also tracks new member signups, we can model the dynamic relationship between this form of word-of-mouth and the addition of new members to the social networking site. These members are, in a real sense, also the "customers" of the social networking site, as their exposure to advertising while using the site produces revenue for the firm.

Internet companies commonly employ several types of WOM marketing activities. The major categories include the following:

1) Viral Marketing – creating entertaining or informative messages designed to be passed on by each message receiver, analogous to the spread of an epidemic, often electronically or by email;

2) Referral Programs – creating tools that enable satisfied customers to refer their family and friends; and

3) Community Marketing – forming or supporting niche communities that are likely to share interests about the brand (such as user groups, fan clubs, and discussion

forums) and providing tools, content, and information to support those

communities.[1]

In this paper, we will focus on electronic referrals, one specific form of WOM activity in the

referral program category listed above.

The goal of this research is to model and estimate the nature of the dynamic relationship

between new member acquisition and WOM referrals based on detailed time series data from an

Internet social networking site. In so doing, we will estimate the elasticity, both short and long-

run, for word-of-mouth referral activity at the site. We will also compare these elasticity

estimates with those obtained for media appearances (public relations) and event marketing – the

main company-sponsored marketing activity.

In our modeling approach we also recognize the potential endogeneity in customer

acquisition, WOM activity, and other marketing communication efforts. WOM may be

endogenous because it not only influences new customer acquisition but is itself affected by the

number of new customers. Likewise, traditional marketing activities may stimulate WOM; they

should be credited for this indirect effect as well as the direct effect they may have on customer

acquisition. We will empirically test for this endogeneity using Granger causality tests. We then

develop a Vector Autoregression (VAR) model to handle the endogeneity. We link variation in

the number of newly acquired customers (signups) with the number of invitations (referrals) sent

by existing members of the network to their friends outside the network. The proposed model

allows us to measure the short and long-run effects of WOM and to compare the effects of WOM

with those of other marketing communications.

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[1] The interested reader can find a detailed overview of different forms of WOM marketing available at the Word of
Mouth Marketing Association web site (www.womma.org).

Our empirical results show that WOM referrals strongly affect new customer acquisitions at the social networking site. We estimate a long-run elasticity of 0.53. This is approximately 2.5 times higher than the average advertising elasticity reported in the literature (e.g. Hanssens et al 2001). For the company we study, WOM has a much stronger impact on new customer acquisition than traditional forms of marketing. In particular, WOM elasticity is about 20 times higher than the elasticity for marketing events (0.53 vs. 0.026). We translate these findings into monetary implications by calculating how much the average newly acquired customer contributes to firm revenues. This provides an upper bound to the financial incentives the firm might consider offering to existing customers to stimulate outbound word-of-mouth. We note that the practice of seeding or stimulating word-of-mouth has grown rapidly in recent use but that quantifying the effectiveness or returns of this activity remains difficult (e.g., Godes et al 2004).

Research Background

The earliest study on the effectiveness of WOM is survey-based (Katz and Lazarsfeld 1955). The authors found that WOM was seven times more effective than print advertising in influencing consumers to switch brands. Since the 1960s, word of mouth has been the subject of more than 70 marketing studies (Money et al 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 influence people have on their peers in WOM communications. Consumer influence over other consumers has been demonstrated in scholarly research concerning social and

communication networks, opinion leadership, source credibility, uses and gratifications, and diffusion of innovations (Phelps et al 2004).

Until recently, WOM research relied primarily on experimental methods versus studying actual consumer actions in the marketplace. A major challenge in studying actual WOM is obtaining accurate data on interpersonal communications. Examining WOM on the Internet can help address this problem by offering an easy way to track online interactions. The Internet, of course, gives only a partial view of interpersonal communication; WOM exchange is not limited to the online world. Nevertheless, for some products or product categories, Internet measures of WOM could be a good proxy for overall WOM. We believe that for *online* communities, the electronic form of "spreading the word" is the most natural one. This leads us to suggest that online WOM should be a good proxy for overall WOM in the Internet social network setting of our study.

Recent research has begun to study WOM in an Internet setting. De Bruyn and Lilien (2004) observed the reactions of 1,100 recipients after they received an unsolicited email invitation from one of their acquaintances to participate in a survey. They found that the characteristics of the social tie influenced recipients' behaviors but had varied effects at different stages of the decision-making process: 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. Godes and Mayzlin (2004) suggest that online conversations (e.g., Usenet posts) could offer an easy and cost-effective opportunity to measure word of mouth. In an application to new television shows, they linked the volume and dispersion of conversations across different Usenet groups to offline show ratings. Chevalier and Mayzlin (2006) used book reviews posted by customers at Amazon.com and BarnesandNoble.com online

stores as a proxy for WOM. The authors found that while most reviews were positive, an improvement in a book's reviews led to an increase in relative sales at that 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). Finally, Villanueva, Yoo and Hanssens (2006) compared customer lifetime value (CLV) for customers acquired through WOM vs. traditional channels. In an application to a web hosting company, the authors showed that customers acquired through marketing add more short-term value to the firm, but customers acquired by word-of-mouth added nearly twice as much long-term value. However, the authors did not observe the firm's marketing activity. Thus, the response of customer acquisition to WOM and traditional marketing activity could not be directly estimated.

Our paper differs from above studies in research question and application. First, we aim to directly compare the dynamic effects of word-of-mouth referrals with those of traditional marketing efforts. In so doing, we will also attempt to quantify the monetary value of each WOM referral to the firm. Second, our empirical application is to an Internet social networking site which provides a set of substantive findings in a novel marketing setting.

Internet Social Networking Sites

While still a relatively new Internet phenomenon, online social networking has already attracted attention from major Internet corporations. Microsoft, Google, Yahoo! and AOL are among companies offering online community services. According to Wikipedia (www.wikipedia.org), at present there are about 30 social networking web sites each with more than one million registered users and several dozen significant, though smaller, sites. In terms of web traffic, as of March 2006, ComScore MediaMetrix reports that the largest online social

networking site was MySpace.com with 42 million unique visitors per month, followed by

FaceBook.com with 13 million and Xanga.com with 7.4 million unique visitors. ComScore

MediaMetrix numbers suggest that every second Internet user in the U.S. visits one of the top 15

social networking sites (Table 1).

[Table 1. Social Networking Sites Ranking]

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. Hence, invitations (i.e. WOM referrals) have been

the foremost driving force for sites to acquire new members. Typical social networking sites

allow a user to build and maintain a network of friends for social or professional interaction. In

the core of a social networking site are personalized user profiles. Individual profiles are usually

a combination of users' images (or avatars), list of interests, music, books, movies preferences,

and links to affiliated profiles ("friends"). Different sites impose different levels of privacy in

terms of what information is revealed through profile pages to non-affiliated visitors and how far

"strangers" vs. "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 relation formation also exist.

In contrast to other Internet businesses, online communities rely upon user-generated

content to retain users. A community member has a direct benefit from bringing in more

"friends" (e.g., through participating in the referral program), as 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 non-members to join

the community. Figure 1 shows how two popular social networking sites, Friendster.com and Tribe.com, implement the referral process.

[Figure 1. Referrals Process at Friendster.com and Tribe.com]

Referrals made through the interface provided by the site are easily tracked. Some sites offer incentives to make a referral. For example, Netflix.com recently offered its existing customers the opportunity to pass along a "gift" of a month of free service to their non-member acquaintances. Many subscription-based services offer progressive discounts on monthly fees for each referral made.

While the mechanics of social network formation through the WOM referrals process may be straightforward, little is known about the dynamics and sustainability of this process. Also, as social networking sites mature, they may begin to increase their use of traditional marketing tools. Management therefore may start to question the relative effectiveness of WOM at this stage. Our objective is to contribute a new set of empirical findings on this subject.

Modeling Approach

A social networking site has several ways to attract new customers, including event marketing (directly paid for by the company), media appearances (induced by PR) and word-of-mouth (WOM) referrals. To model the effectiveness of these communication mechanisms, we turn first to a time series regression approach. As a benchmark model, we may regress signups on events, media and WOM, controlling for deterministic components such as a base level (constant), a deterministic (time) trend, seasonality and lags of the dependent variable (Box and Jenkins 1970). The time trend is intended to capture external factors, including growth in Internet access, growth in people with high-speed bandwidth, and general increases in content and

interest in social networking sites. Seasonal patterns may be both high frequency (e.g. day-of-week), as most Internet use occurs during weekdays (Pauwels and Dans 2001), as well as low frequency, e.g., annual holiday periods such as summer vacation. Equation (1) specifies this basic regression model:

$$Y_t = X_t + M_t + E_t + C + T + \sum_{i=1}^{6} d_i + H_t + \sum_{j=1}^{J} Y_{t-j} + \varepsilon_t \qquad (1)$$

where

t = day index,

Y_t = number of signups (new members),

X_t = number of WOM-referrals,

M_t = number of media appearances,

E_t = number of promotional events,

C = constant,

T = deterministic time trend,

d_i = indicators for days of the week (using Friday as the benchmark),

H = holiday indicator (summer vacation),

J = number of lags of the dependent variable needed to ensure the residuals ε_t are white-noise errors (no residual autocorrelation).

Note that equation (1) includes only the immediate effects of marketing actions on signups. To include dynamic effects, we can add lags of the marketing actions, obtaining the following autoregressive-distributed lag (ARDL) model (e.g., Hanssens et al. 2001):

$$Y_t = \sum_{l=1}^{L} X_{t-l} + \sum_{m=1}^{M} M_{t-m} + \sum_{n=1}^{N} E_{t-n} + C + T + \sum_{i=1}^{6} d_i + H_t + \sum_{j=1}^{J} Y_{t-j} + \varepsilon_t \quad (2)$$

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

While model (2) now captures dynamic effects, it does not account for indirect effects of marketing actions on performance. For example, events may directly increase signups, receive media coverage (indirectly benefiting signups), and increase the likelihood that current customers refer others to the site. These new customers may, in turn, invite their friends to join the site (WOM). Finally, the firm's managers may adjust their marketing actions for upcoming periods as they observe the performance of previous marketing campaigns. Figure 2 displays this system of plausible interactions, which may occur immediately (i.e., on the same day in our data), but likely play out dynamically, i.e. over several days.

[Figure 2. Modeling Framework]

The links represented in Figure 2 can be tested by investigating which variables Granger cause other variables (Granger 1969, Hanssens et al. 2001). In essence, Granger causality implies that knowing the history of a variable X helps explain a variable Y, over and above Y's own history. This 'temporal causality' is the closest proxy for causality that can be gained from studying the variables' time series; in the absence inducing causality in controlled experiments. We perform a series of Granger causality tests on each pair of key variables. We note that 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 in whether we can rule out that X Granger causes Y at any lag. Therefore, we will run the causality tests for lags up to 20 and report the results for the lag that has the highest significance for Granger causality.

If signups do Granger cause (some of) the marketing variables, we need to capture the complex interactions of Figure 2 in a full dynamic system. To this end, we specify and estimate a vector-autoregressive (VAR) model. Compared to alternative specifications, VAR models are especially well suited to measure dynamic interactions among performance (signups) and marketing variables and to estimate the dynamic response of signups to both WOM and traditional marketing actions. Recently, VAR models have been used to analyze a wide variety of long-term marketing effects – including advertising, price promotions and new product introductions (e.g., Dekimpe and Hanssens 1999; Pauwels et al. 2002, 2004; Srinivasan et al. 2004).

VAR Model Specification

We propose a four-variable VAR system to capture the dynamic interactions between signups, WOM (invitations), and traditional marketing (media appearances and promotional events). Equation (3) displays the model:

$$
\begin{bmatrix} Y_t \\ X_t \\ M_t \\ E_t \end{bmatrix} = \begin{bmatrix} C_Y \\ C_X \\ C_M \\ C_E \end{bmatrix} + \begin{bmatrix} \delta_Y \\ \delta_X \\ \delta_M \\ \delta_E \end{bmatrix} \times T + \begin{bmatrix} \theta_Y \\ \theta_X \\ \theta_M \\ \theta_E \end{bmatrix} \times H + D \begin{bmatrix} \gamma_Y \\ \gamma_X \\ \gamma_M \\ \gamma_E \end{bmatrix} + \sum_{j=1}^{J} \begin{bmatrix} \phi_{11}^j & \phi_{12}^j & \phi_{13}^j & \phi_{14}^j \\ \phi_{21}^j & \phi_{22}^j & \phi_{23}^j & \phi_{24}^j \\ \phi_{31}^j & \phi_{32}^j & \phi_{33}^j & \phi_{34}^j \\ \phi_{41}^j & \phi_{42}^j & \phi_{43}^j & \phi_{44}^j \end{bmatrix} \begin{bmatrix} Y_{t-j} \\ X_{t-j} \\ M_{t-j} \\ E_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Y,t} \\ \varepsilon_{X,t} \\ \varepsilon_{M,t} \\ \varepsilon_{E,t} \end{bmatrix} \quad (3)
$$

where *J* equals the number of lags included (the order of the model), D is the vector of day-of-week dummies and ε_t are white-noise disturbances distributed as $N(0, \Sigma)$.

Note that in equation (3) the vector of endogenous variables -- signups (Y), WOM-referrals (X), media appearances (*M*) and promotional events (*E*) -- is also related to its own past, which allows complex dynamic interactions among these variables. The vector of exogenous variables includes (i) an intercept *C*, (ii) a deterministic-trend variable *T*, to capture the impact of omitted, gradually changing variables, (iii) indicators for days of the week *D*, and (iv) seasonal

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(e.g., Holidays) dummy variables *H*. Instantaneous effects are captured by the variance-covariance matrix of the residuals Σ. In the absence of cointegration (i.e., the existence of a linear combination between evolving variables which results in stable residuals), vector autoregressive (VAR) models are estimated with the stationary variables in levels and the evolving variables in differences.

VAR modeling is commonly applied to quantify short- and long-run market response (Dekimpe and Hanssens 1999). We note two features of this approach. First, the endogenous treatment of WOM implies that it also is explained by its own past and the past of the signups variable. In other words, this dynamic system model estimates the baseline of each endogenous variable and forecasts its future values based on the dynamic interactions of all jointly endogenous variables. Permanent effects are possible for evolving performance variables, and statistical criteria such as the Akaike Information Criterion (AIC) suggest lag lengths *J* that balance model fit and complexity (Lutkepohl 1993). Second, dynamic effects are not *a priori* restricted in time, sign, or magnitude. The sign and magnitude of any dynamic effect need not follow any particular pattern – such as the imposed exponential decay pattern from Koyck-type models (see Pauwels et al. 2002 for a detailed discussion).

Testing for Evolution or Stationarity: Unit-Root Tests

We perform unit root tests to determine whether the endogenous variables are stable (fluctuate temporarily around a fixed mean) or evolving (have no fixed mean and can deviate permanently from previous levels). The results of the unit root analyses will subsequently affect the model estimation procedure. We use both the Augmented Dickey-Fuller test procedure recommended by Enders (1995) and the Kwiatkowski-Phillips-Schmidt-Shin test (1992). The former maintains evolution as the null hypothesis (and is the most popular in marketing

applications), while the latter maintains stationarity as the null hypothesis. Convergent

conclusions of these two tests yield higher confidence in our variable classification (Maddala and

Kim 1998). In our case, results of both tests confirmed trend stationarity in all series (i.e., all

series appeared stationary after controlling for deterministic trend). Thus, we conclude that VAR

estimations can be performed with the variables in levels.

Impulse Response Functions

Because it is infeasible to interpret estimated VAR-coefficients directly (Sims 1980),

researchers use the estimated coefficients to calculate impulse response functions (IRFs). The

IRF simulates the over-time impact of a change (over its baseline) to one variable on the full

dynamic system and thus represents the net result of all modeled actions and reactions (see

Pauwels 2004 for an elaborate discussion). 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). In the context of our

research questions, we use impulse response functions to disentangle the short and the long-run

effects of WOM and traditional marketing on signups. Consistent with previous 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 published in marketing.

Empirical Analysis

Data Description

We applied our model to data from one of the major social networking sites, which wishes to remain anonymous. The dataset contains 36 weeks of daily numbers of signups and referrals (provided to us by the company) along with marketing events and media activity (obtained from 3rd party sources). The data cover the period from February 1 to October 16, 2005. Figures 3 and 4 show time plots for all four variables and Table 2 provides descriptive statistics.

[Figure 3. Time Series: Signups, Invitations]

[Figure 4. Time Series: Media and Marketing events]

[Table 2. Descriptive Statistics]

During the observation period, the daily signups and WOM-referrals showed a positive trend. We observed somewhat lower activity in referrals over the summer season (as practiced in the U.S. - June 20 through Labor Day, which was September 5 in 2005). Over the 36 weeks, the company organized or co-sponsored 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 services (www.factiva.com). We did not use the content of these publications; thus, our measure of media activity is coarse. In a more general case it would be important to account for the valence of the message (as Godes and Mayzlin (2004) report for TVshows). In our study, however, given the relatively young age of the company, we did not have a reason to believe that a significant share of the publications had a

negative tone. Moreover, we removed a few negative "suspects" from the sample as judged by the title of the publication.[2] In sum, we feel the number of media appearances is a useful measure for our research purpose.

Direct Effects of Marketing on Signups

We first present the results from estimating the benchmark time series regression models given in equations (1) and (2). These models regress signups against WOM referrals, media, and events, while controlling for a time trend, day-of-week, and seasonality. Results from both models are presented in Table 3. The left column of parameter estimates corresponds to the specification for immediate effects only (equation 1) while the right column corresponds to the carry-over effects specification (equation 2). The models are estimated in log form, which provides direct results for the elasticities from the estimated coefficients.

[Table 3 Regression Analysis Results]

Across both regression models, we find high explanatory power ($R^2 = .932$) and the expected signs for marketing actions (positive), trend (positive) and seasonality (positive for weekdays and for the summer break, negative for the weekend). Moreover, we find similar effect magnitudes for the two models. WOM has the largest elasticity (0.14), about 75 times larger than that for events (0.002), while media appearances do not significantly increase signups. Because all dynamic effects (equation 2) and potential interaction effects (results available upon request) are insignificant, adding them does not change our substantive findings. Indeed, the model in equation (1) outperforms more complex models based on both adjusted R^2 and the Akaike Information Criterion (AIC).

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[2] The removal of these events did not have a significant impact on estimation results.

Endogeneity (Granger Causality Test Results)

We summarize the results from the Granger Causality tests in Table 4. Each cell gives the minimum p-value obtained from the causality tests conducted from one lag to 20 lags.

[Table 4 Granger Causality Test Results]

The results in Table 4 clearly indicate that endogeneity is present among the variables in our data. As expected, Granger causality is detected for WOM referrals, media and events on signups (the direct effects). In addition, Granger causality is also found for many of the other pairings. For example, signups Granger cause WOM referrals (the interdependent effect argued earlier), events (indicating management performance feedback, e.g. Dekimpe and Hanssens 1999), and media (indicating that spikes in signups may receive media attention). Moreover, events Granger cause media (indicating that media covers events) and media Granger causes events (indicating that management may seek to time events to match pending media coverage). On the other hand, WOM-referrals do not Granger cause events or media appearances (as the media does not observe referrals directly) and media appearances do not Granger cause WOM. In sum, the results from the Granger causality tests indicate the need to consider the full dynamic system, as in a VAR-model, and account for the indirect effects of marketing actions.

VAR Model Selection and Estimation

Our VAR-model selection starts with the four endogenous variables (number of daily signups and WOM-referrals, media appearances, promotional events) and a deterministic trend *t,* which captures the firm's growth during the observation period. Next, we add day of the week effects, and then a holiday effect. The model fit results are presented in Table 5. The AIC criterion suggests that the best model includes all of the proposed effects. Finally, we note that the AIC criterion selects 2 as the optimal lag length.

[Table 5 VAR Model Fit Results]

Using the VAR system parameters, we compute a series of impulse response functions

The impulse response functions (IRFs) trace the incremental effect of a one-standard deviation

shock in WOM, events and media on the future values of signups. These enable us to examine

the dynamic effects of each activity on signups, fully accounting for the indirect effects of these

activities. Figures 5a, 5b and 5c plot these impulse response functions.

[Figure 5. Impulse Response Functions]

We look first at Figure 5a, the IRF for signups with respect to a shock in referrals. The

graph shows that it takes approximately three weeks for signups to stabilize after a one standard

deviation shock on referrals (WOM). After 20 days, the IRF bands begin to cross zero, indicating

that further effects are not significant. Turning to Figures 5b and 5c, we do find significant

shorter-term effects for media and events, but stabilization occurs within just a few days. Thus,

compared to traditional marketing activities, the WOM induces both a larger short-term response

as well as a substantially longer carryover effect. The IRF results highlight the need for

researchers to employ models which can also estimate longer-term effects for word-of-mouth

marketing.

Long-term Elasticity of Marketing Actions

To quantify the long-run elasticity of referrals (and the other marketing actions) on

signups, we calculate arc elasticities using the following approach. First, from the IRF analysis,

we compute the total change in number of signups, ΔY, in response to a one standard deviation

shock to WOM referrals. Second, using our data, we calculate the standard deviation for word-

of-mouth referrals (σ_X) and mean values for signups ($\bar{Y}$) and WOM-referrals ($\bar{X}$). Lastly, we

then use equation (4) to calculate the arc elasticity, η_{arc}:

$$\eta_{arc} = \frac{\Delta Y}{\sigma_X} \times \frac{\overline{X}}{\overline{Y}} . \qquad (4)$$

Note that equation (4) is a standard elasticity formula, except that σ_X is substituted for ΔX. This

follows because σ_X the change in X that is used to generate the IRF. The results of the elasticity

computations are displayed in Table 6. In the table, we present results at 1 day, 3 days, 7 days

and the total long-term elasticity.

[Table 6 Elasticity of Signups to Marketing Activities]

The results for the short-run or immediate elasticities in Table 6 can be compared with

those obtained from the regression analyses (Table 3). Note that the VAR-based elasticities for

media and events are higher than the regression-based elasticities. This difference is likely due

to the fact that the VAR-model accounts for the indirect benefits produced by the traditional

marketing activities are also taken into account. In contrast, WOM-referrals have a smaller short-

term elasticity in the VAR setting. This suggests that some of the estimated short-run effect size

in the regression could be due to the firm's other marketing actions, which affect both WOM and

signups in the same day.

Looking at the longer-term elasticities, it indeed appears that WOM-referrals are akin to

the "gift that keeps on giving." Due to the slow decay rate, the 3-day, 7-day and total long-term

elasticities are all higher than the regression-based estimates. In the long-run, Table 6 shows that

the elasticity of WOM referrals (0.53) is about 20 times higher than the elasticity for marketing

events (0.53 vs. 0.026) and 30 times higher than the elasticity for media appearances (0.53 vs.

0.017).

In sum, the long-term elasticity obtained from the VAR-model is higher than the direct

effect calculated from the regression models (equations 1 and 2). This indicates the importance

of accounting for the indirect effects illustrated in Figure 2. It is interesting to note that the direct

WOM elasticity (estimated from regression) is close to the average advertising elasticity of 0.10

to 0.20 reported in the literature (e.g., Hanssens et al 2001), but that the total long-run elasticity

is several times higher. Part of this may be due to the fact that previous studies often account

only for the direct effects of advertising and do not incorporate indirect benefits such as

increasing retailer support (e.g., Reibstein and Farris 1995) and increasing investor awareness

(e.g., Joshi and Hanssens 2006).

Managerial Implications: Monetary Value of WOM Referrals

      Several authors suggest that companies should actively try to create WOM

communication (Godes and Mayzlin 2004, Liu 2006, Rosen 2000). To this end, a growing

practice in both offline and online markets is to offer financial incentives to existing customers.

Important input for such a referral program would be the value a WOM communication provides

to the firm. To this end, we conduct a simulation to highlight the monetary implications from

inducing additional WOM by offering financial incentives to existing customers. Our simulation

is based on the economics of the online advertising business model, which is standard to many

social networking sites. In this model, each new customer acquisition translates into an expected

number of banner ad exposures. For the simulation, we use industry averages for cost per

thousand impressions (CPM) and number of impressions per user/day while making assumptions

regarding customer's projected lifetime with the firm. Marketing practitioners should use these

results with caution as the suggested measures may vary greatly across firms. Other online

advertising models such as pay per click (PPC), pay per lead (PPL), and pay per sale (PPS) could

be incorporated in this analysis in a similar manner by substituting the appropriate conversion

rates.

While CPM on some premium sites could reach as much as $15, for most social networking sites, CPM does not exceed a dollar. We have obtained price quotes from several social networking sites and concluded that about 40 cents per thousand impressions is a reasonable number. According to Nielsen//NetRatings (2005), the average number of pages viewed on a community site by a unique visitor per month is about 130. From what we have observed across multiple social networking sites, the average page carries about 2 to 3 ads. Accordingly, the average user contributes approximately 13 cents per month or approximately $1.50 a year. From the IRF analysis, we estimated a long-run marginal effect of WOM of 0.52 or, in words, 10 WOM-referrals bring in approximately 5 new site members over the course of 3 weeks.[3] From the above we conclude that each invitation sent is worth about 75 cents per year. By sending out 10 invitations, each network member could bring about $7.50 to the firm. Management can use this number as a starting point to plan a referral incentive program.

Conclusions and Future Research

In this study, we proposed an approach to evaluate the effectiveness of electronic word-of-mouth. Specifically, we attempted to quantify the elasticity of referral marketing in an application to an online social community site. For the collaborating site, we tracked actual outgoing WOM-referrals recorded electronically, matched them with new customer additions and quantified short run and long run effects. Using a Vector Autoregression (VAR) model, we showed that WOM referrals have a very strong impact on new customer acquisition. WOM referrals were about 2.5 times higher than the average advertising elasticity reported in the literature. In addition, our estimated WOM effect on new customer acquisition is also larger

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[3] Note that in our dataset the ratio of daily average number of signups to the daily average number of WOM-referrals is close to one (Table 2). Accordingly, the estimation of long-run marginal effect of WOM (0.52) appears to be not significantly different from the estimation of WOM elasticity (0.53).

than that of traditional forms of marketing. In particular, WOM is about 20 times higher than the elasticity for marketing events (0.53 vs. 0.026) and 30 times higher than the elasticity for media appearances (0.53 vs. 0.017). We also conducted a simulation to highlight the monetary implications from inducing additional WOM by offering financial incentives to existing customers. Our results suggest that social networking firms with a primary stream of revenues coming from online advertising should be willing to pay about 75 cents for each referral.

Our research also has several limitations. First, our data come from one social networking site during one period in the site's existence. This means that further research is needed to examine whether our findings generalize to other companies and settings. In this regard, we note that, in a review of 23 service categories, East *et al.* (2005) found that WOM had greater reported impact on brand choice than advertising or personal search. Second, data limitations prevent us from analyzing the effects of WOM for - and marketing actions by - competing sites, a situation typical for these types of company data sets. Third, our model is in reduced form. This implies that the long-run impact calculations are subject to the assumption that the basic data-generating process does not change. This is appropriate for "innovation accounting," i.e., identifying and quantifying the effects of WOM and traditional marketing on signups in the data sample (Franses 2005; van Heerde, Dekimpe, and Putsis 2005). The modeling approach is not suited for revealing structural aspects of subscriber and company behavior.

When a company stimulates WOM activity, we note that it is no longer "organic" word-of-mouth. Indeed, one might term it "fertilized" word-of-mouth. We do not know whether fertilized word-of-mouth would produce the same elasticity as the organic word-of-mouth observed in our data. If the paid nature of WOM activity is known, fertilized word-of-mouth may be substantially less effective than organic word-of-mouth. In this respect, our monetary value

calculations may represent an upper bound of the money that could be generated by stimulating word-of-mouth. On the other hand, our data may miss some benefits from increasing word-of-mouth. These could include signups not attributed to a referral (i.e., not captured in the referral process or self-reported at signup). Finally, our simulation does not consider other important aspects of customer lifetime value such as the impact that one user may have on retention and site usage by other existing network members. Metcalfe's law (e.g., Reed 1999) states that the value of a network is proportional to the square of the number of users of the system. Our approach does not evaluate customer value beyond what can be attributed to a larger volume of generated referrals. Thus, one logical next step would be to develop an individual level model which allows for user-specific contributions to the network.

In sum, this paper sheds new light on "the world's most effective, yet least understood marketing strategy" (Misner 1999) by quantifying the dynamic performance effects of word-of-mouth in an Internet setting which offers direct ways of observing this phenomenon. Our results demonstrate the monetary value of word-of-mouth in this context and illustrate the importance of accounting for other marketing activities and feedback effects that help explain the expansion of social networking sites.

Table 1

Ranking of Internet Social Networking Sites

Social Networking Sites	Number of Visitors (in thousands)
MYSPACE.COM	41,889
FACEBOOK.COM	12,917
XANGA.COM	7,448
LIVEJOURNAL.COM	4,047
Yahoo! 360°	3,614
MYYEARBOOK.COM	3,613
HI5.COM	2,609
TAGWORLD.COM	2,275
TAGGED.COM	1,668
BEBO.COM	1,096
FRIENDSTER.COM	1,066
Tribe	871
43THINGS.COM	661
SCONEX.COM	372
Internet Total	*171,421*

Source: ComScore MediaMetrix, March 2006 Report

Table 2

Descriptive Statistics[4]

	Mean	*Median*	*Maximum*	*Minimum*	*Std. Dev.*
Signups	11.36	11.30	11.89	10.86	0.29
WOM-referrals	11.37	11.42	12.09	10.53	0.38
Media	0.92	0	8	0	1.34
Events	0.39	0	4	0	0.64

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[4] The numbers reported in Table 2 have been monotonically transformed to preserve the anonymity of the collaborating site. Actual data were used in econometric analysis.

Table 3

Regression Analysis Results

Dependent Variable: Log of Signups

	Equation 1 (immediate)	Equation 2 (carry-over)
LogWOMReferrals	0.141	0.136
	(6.38)*	(5.79)
LogMEDIA	0.000	0.000
	(.57)	(0.39)
LogEVENTS	0.002	0.002
	(2.06)	(2.13)
LogWOMReferrals(-1)		0.013
		(0.57)
LogMEDIA(-1)		0.000
		(0.26)
LogEVENTS(-1)		0.001
		(0.97)
Constant	9.305	9.208
	(36.88)	(29.91)
Time Trend	0.003	0.003
	(24.91)	(23.89)
Monday	0.093	0.098
	(5.96)	(5.79)
Tuesday	0.058	0.063
	(3.16)	(3.05)
Wednesday	0.032	0.034
	(1.68)	(1.67)
Thursday	0.013	0.015
	(0.69)	(0.74)
Saturday	-0.053	-0.050
	(-2.93)	(-2.66)
Sunday	-0.085	-0.083
	(-5.34)	(-5.01)
Summer	0.136	0.140
	(6.09)	(6.00)
Lagged dependent variable	0.453	0.451
	(7.92)	(7.82)
R^2	.932	.932
Adjusted R^2	.929	.928
Akaike Information Criterion	-2.248	-2.225

*t-statistics in parenthesis

Table 4

Results of the Granger Causality Tests

(Minimum p-values Across 20 lags)

Dependent Variable Is Granger caused by:	Signups	WOM-referrals	Media	Events
Signups		.02[*]	.00	.00
WOM referrals	.00		.22	.08
Media	.00	.58		.02
Events	.02	.00	.01	

[*] Read as WOM-referrals are Granger caused by Signups at the .02 significance level.

Table 5

VAR Model Fit Results

	Log likelihood	AIC

Model without seasonality:
    signups, WOM-referrals, media, events
    intercept, deterministic trend
	-6165.59	48.48

With day of the week effect:
    signups, WOM-referrals, media, events
    intercept, deterministic trend,
    day of the week
	-6096.28	48.13

With holiday effect:
    signups, WOM-referrals, media, events
    intercept, deterministic trend,
    day of the week, holiday
	-6083.15	48.06

Table 6

Short-Term Versus Long-Term Elasticity of Signups to Marketing Activities

	1 day	3 days	7 days	Long term
WOM Referrals	0.068	0.171	0.330	0.532
Media	0.008	0.017	0.017	0.017
Events	0.008	0.022	0.026	0.026

Figure 1a. Referrals Process at Friendster.com
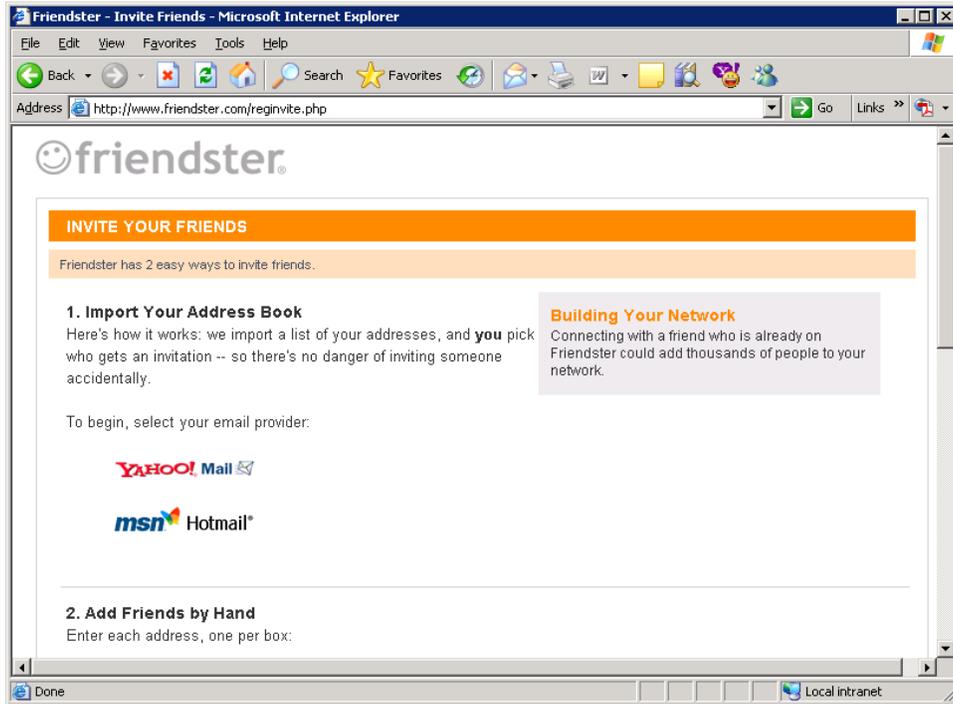
Figure 1b. Referrals Process at Tribe.com
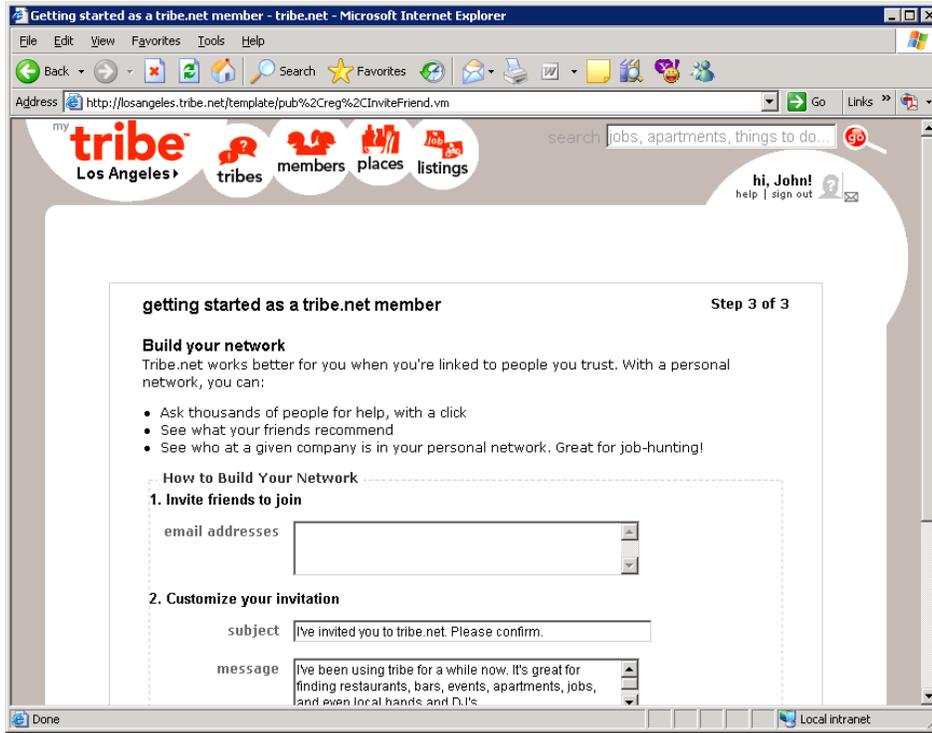
Figure 2

Modeling Framework
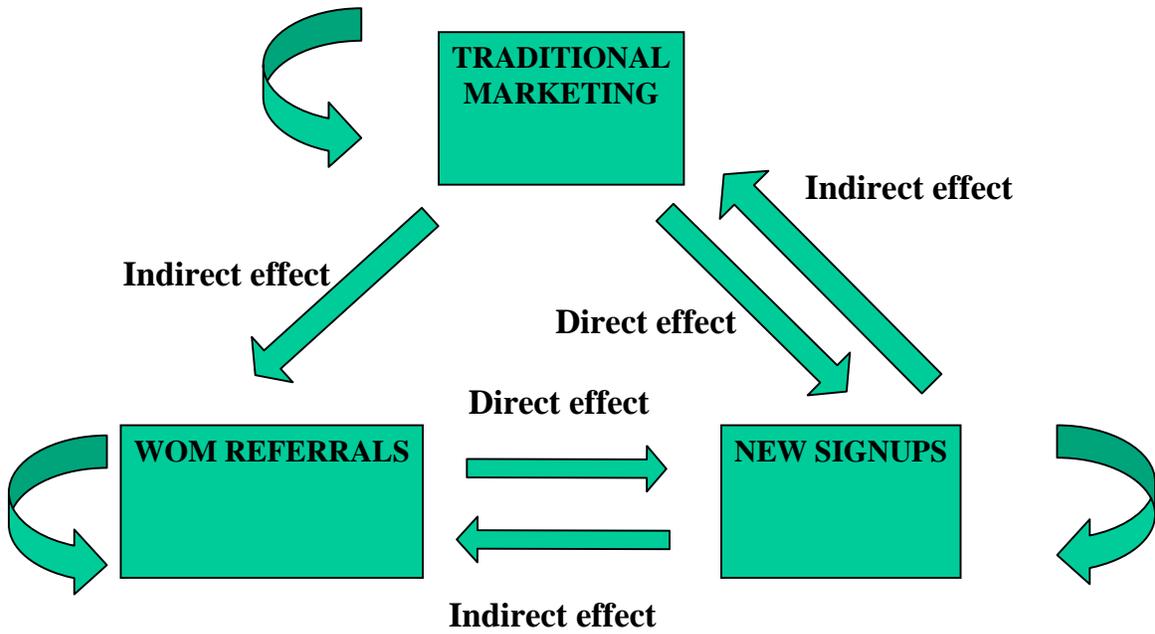
Figure 3a. Time Series: WOM Referrals[5]

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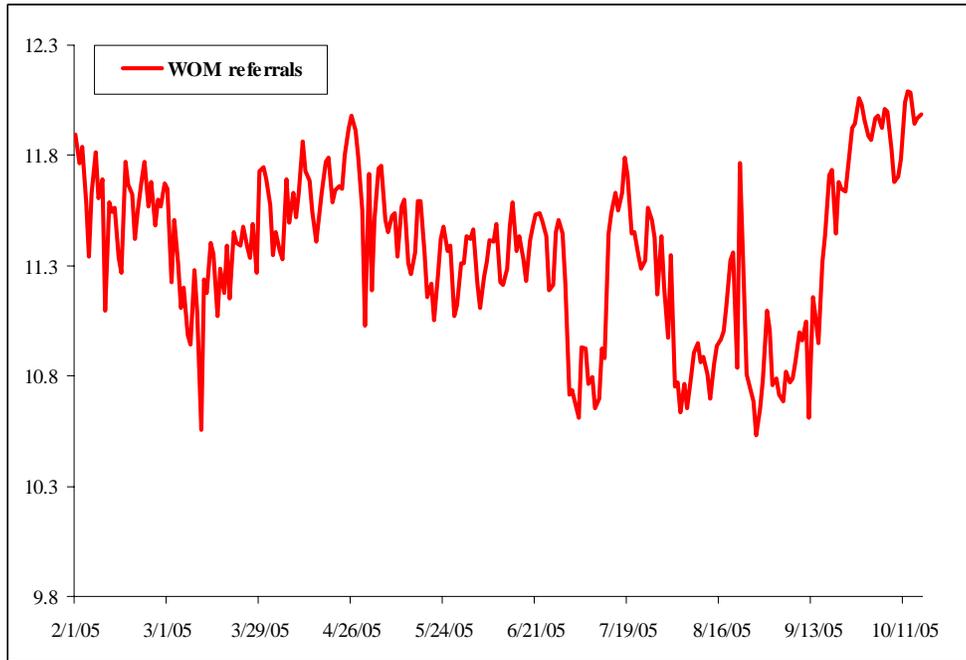
[5] The numbers reported in Figures 3(a-b) and Figure 5(a-c) have been monotonically transformed to preserve the anonymity of the collaborating site. Actual data were used in econometric analysis.

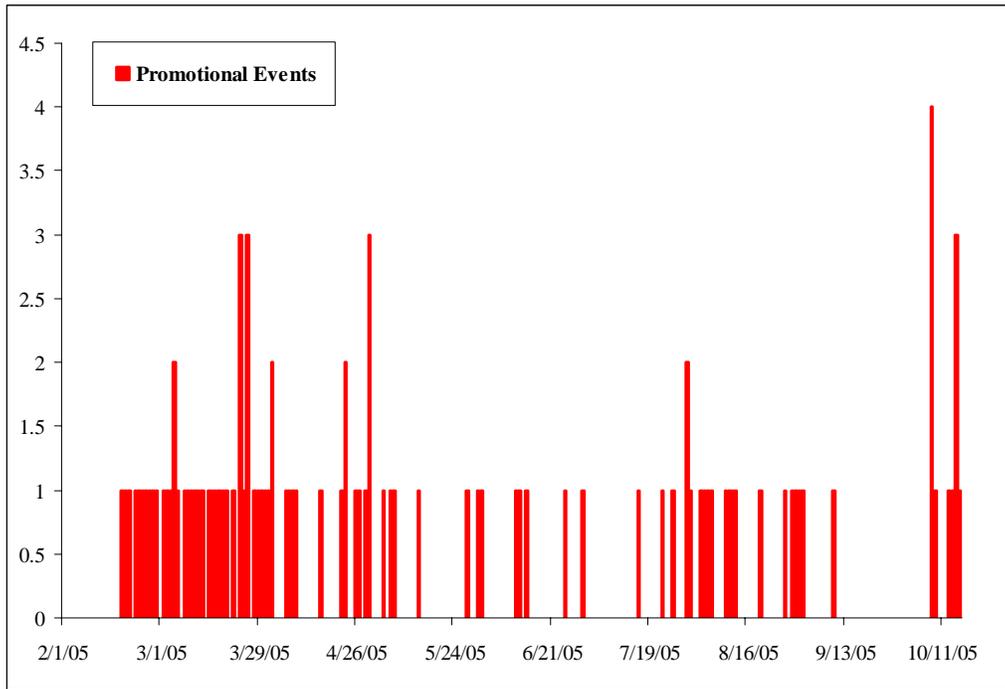**Figure 3b. Time Series: Signups**
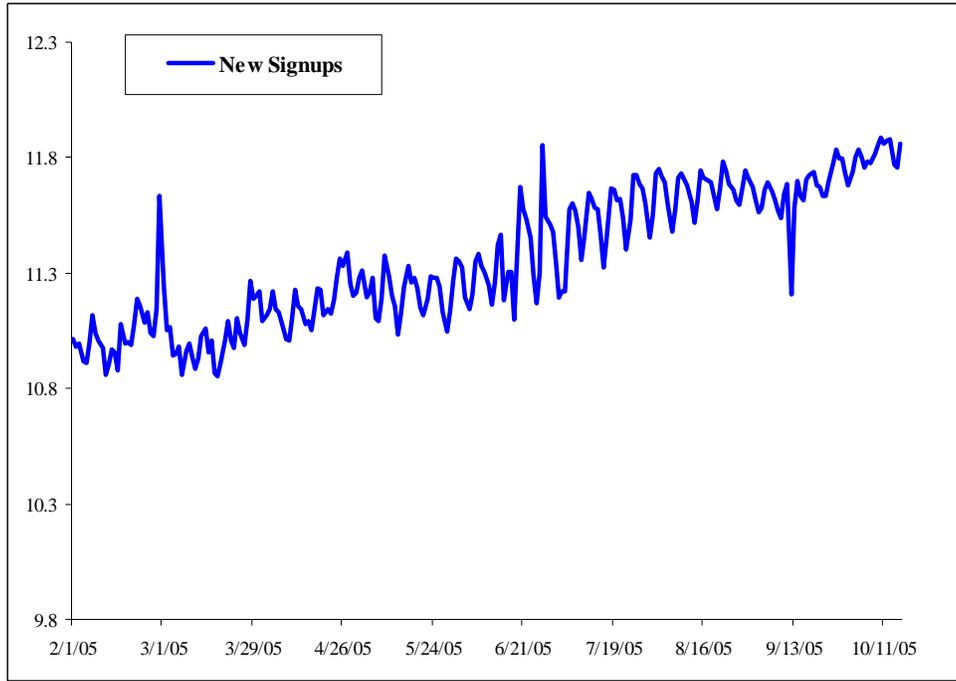
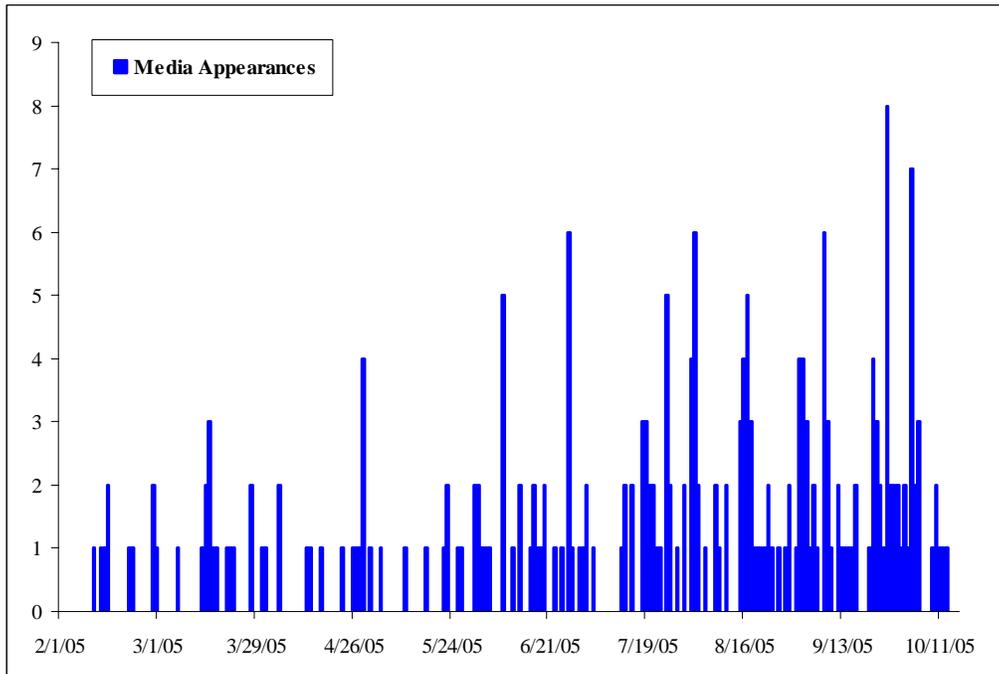**Figure 4a. Time Series: Promotional Events**

Figure 4b. Time Series: Media Appearances

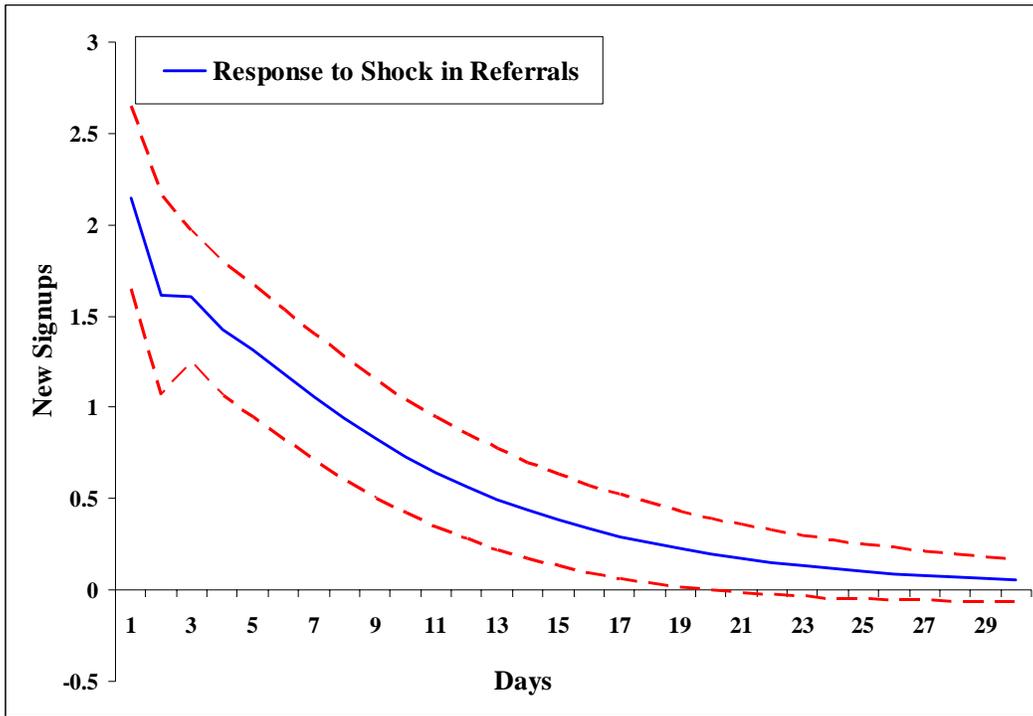**Figure 5a. IRF: Response of Signups to Shock in Referrals**

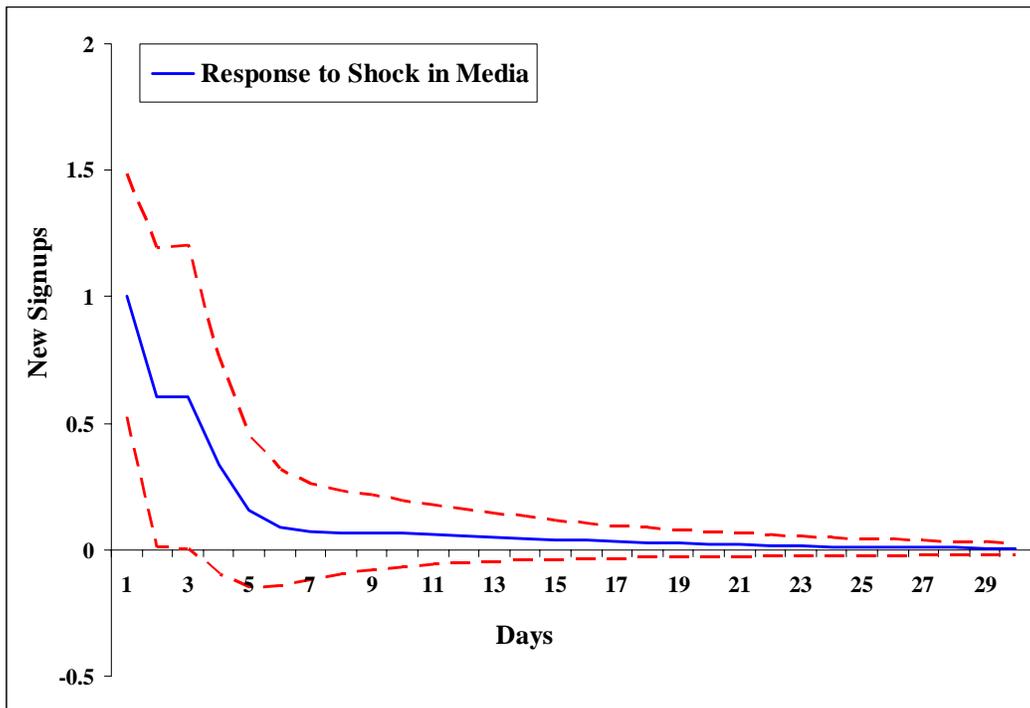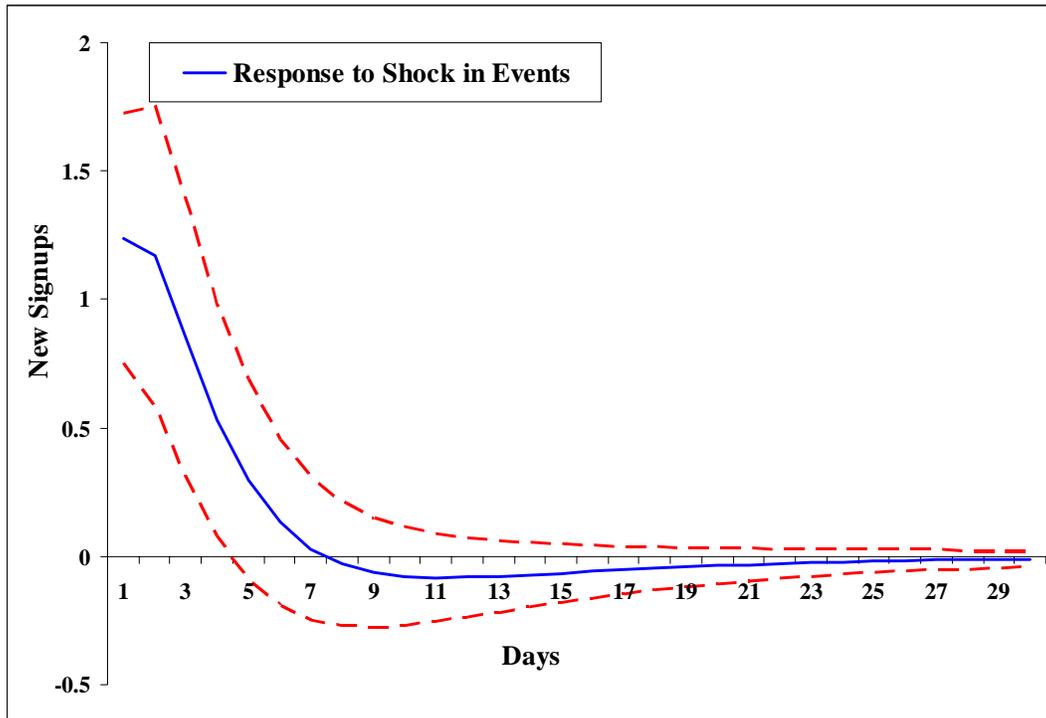**Figure 5b. IRF: Response of Signups to Shock in Media**

Figure 5c. IRF: Response of Signups to Shock in Promotional Events

References

Box, George E.P. and Gwilym M. Jenkins (1970), *Time series analysis: Forecasting and control,* San Francisco: Holden-Day.

Chevalier, Judith, and Dina Mayzlin (2006), "The Effect of Word of Mouth Online: Online Book Reviews," *Journal of Marketing Research*, 43 (August), 345-354.

comScore Media Metrix (2006), "Total Number of Unique Visitors to Selected Social Networking Sites, as of March 2006," (accessed May 22, 2006), [available at http://www.emergencemarketing.com/archives/2006/05/social_networking_sites_d.php].

De Bruyn, Arnaud, and Gary L. Lilien (2004), "A Multi-Stage Model of Word of Mouth Through Electronic Referrals," eBusiness Research Center Working Paper, February, 2004.

Dekimpe, Marnik, and Dominique M. Hanssens (1995), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14(1), 1-21.

Dekimpe, Marnik, and Dominique M. Hanssens (1999), "Sustained Spending and Persistent Response: a New Look at Long-term Marketing Profitability," *Journal of Marketing Research*, 36 (November), 397-412.

East, Robert, Kathy Hammond, Wendy Lomax, and Helen Robinson (2005), "What is the effect of a recommendation?" *Marketing Review*, 5, 2, 145-157.

Enders, Walter (1995), *Applied Econometric Time Series*, Wiley, New York.

Forrester Research (2005), "What's The Buzz on Word-Of-Mouth Marketing? Social Computing and Consumer Control Put Momentum into Viral Marketing," May (2005), www.forrester.com.

Franses, Philip Hans (2005), "On the Use of Econometric Models for Policy Simulation in Marketing," *Journal of Marketing Research*, 42, 4-14.

Godes, David, and Dina Mayzlin (2004), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science*, 23 (4), 545-560.

Godes, David, Dina Mayzlin, Yubo Chen, Sanjiv Das, Chrysanthos Dellarocas, Bruce Pfeiffer, Barak Libai, Subrata Sen, Mengze Shi, and Peeter Verlegh (2005), "The Firm's Management of Social Interactions," *Marketing Letters*, 16:3/4, 415–428.

Granger, Clive W.J. (1969), "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica*, 37, 424–438.

Hanssens, Dominique M. (1980), "Market Response, Competitive Behavior, and Time Series Analysis", *Journal of Marketing Research*, 17 (November), 470-485.

Hanssens, Dominique M., Leonard J. Parsons, and Randall L. Schultz (2001), *Market Response Models: Econometric and Time-Series Research*, 2nd ed. Kluwer Academic Publishers, Boston, MA.

Joshi, Amit and Dominique M. Hanssens (2006), "Advertising Spending and Market Capitalization," MSI Report No. 04-110.

Katz, Elihu, and Paul F. Lazarsfeld (1955), *Personal Influence; The Part Played by People in the Flow of Mass Communications*, Glencoe, Ill. Free Press.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992), "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We that Economic Time Series Have a Unit Root?" *Journal of Econometrics*, 54(1-3), 159-178.

Liu, Yong (2006), "Word-of-Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing*, Vol. 70, July 2006, 74-89.

Lutkepohl, Helmut (1993), *Introduction to Multiple Time Series Analysis*, Springer-Verlag, Berlin, Germany.

Misner, Ivan R. (1999), *The World's Best Known Marketing Secret: Building Your Business with Word-of-Mouth Marketing*, 2nd ed. Bard Press, Austin, TX.

Maddala, G.S. and I.M. Kim (1998), *Unit Roots, Cointegration, and Structural Change*, Cambridge, University Press, Cambridge.

Money, Bruce R., Mary C. Gilly, and John L. Graham (1998), "Explorations of National Culture and Word-Of-Mouth Referral Behavior in the Purchase of Industrial Services in the United States and Japan," *Journal of Marketing*, 62 (4), 76-87.

Montgomery, Alan L., Shibo Li, Kannan Srinivasan, and John C. Liechty (2004), "Modeling Online Browsing and Path Analysis Using Click-stream Data," *Marketing Science*, 23(4), 579-595.

Nielsen//NetRatings (2005), "A Community Uprising," February (2005), www.nielsen-netratings.com.

Nijs, Vincent, Marnik Dekimpe, Jan-Benedict E. M. Steenkamp, and Dominique Hanssens (2001), "The Category Demand Effects of Price Promotions," *Marketing Science*, 20(1), 1-22.

Pauwels, Koen (2004), "How Dynamic Consumer Response, Competitor Response, Company Support, and Company Inertia Shape Long-Term Marketing Effectiveness," *Marketing Science*, 23 (4), 596-610.

Pauwels, Koen and Enrique Dans (2001), "Internet Marketing the News: Leveraging Brand Equity from Marketplace to Marketspace," *Brand Management*, 8(4), 303-314

Pauwels, Koen, Dominique Hanssens, and S. Siddarth (2002), "The Long-term Effects of Price Promotions on Category Incidence, Brand Choice and Purchase Quantity," *Journal of Marketing Research*, 39 (November), 421-439.

Pauwels, Koen H., J.Silva-Risso, S.Srinivasan and D.M. Hanssens (2004), "New Products, Sales Promotions and Firm Value: The Case of the Automobile Industry", *Journal of Marketing*, 68 (October), 142-156.

Pesaran, M.H., R. G. Pierse, and K. C. Lee (1993), "Persistence, Cointegration, and Aggregation: A Disaggregated Analysis of Output Fluctuations in the U.S. Economy," *Journal of Econometrics*, 56 (March), 57-88.

Pesaran, M. Hashem, and Yongcheol Shin (1998), "Generalized Impulse Response Analysis in Linear Multivariate Models," *Economics Letters,* Vol.58, 17-29.

Phelps, Joseph E., Lewis, Regina, Lynne Mobilio, David Perry, and Niranjan Raman (2004), "Viral Marketing or Electronic W-O-M Advertising: Examining Consumer Responses to Pass Along Email," *Journal of Advertising Research*, 44(4), 333-348.

Reed, David P. (1999), "Weapon of Math Destruction: a Simple Formula Explains Why the Internet is Wreaking Havoc on Business Models," *Context Magazine*, Spring 1999.

Reibstein, David J. and Paul W. Farris (1995), "Market Share and Distribution: A Speculation, and Some Implications," *Marketing Science,* Special Issue on Empirical Generalizations in Marketing, Vol. 14, 3 (part 2), 1995, 190-202.

Rosen, Emmanuel (2000), *The Anatomy of Buzz: How to Create Word-of-Mouth Marketing*, New York: Doubleday.

Sims, Christopher A. and Tao Zha (1999), "Error Bands for Impulse Responses," *Econometrica*, 67 (5), 1113-1155.

Srinivasan, Shuba, Koen Pauwels, Dominique M. Hanssens, and Marnik G. Dekimpe (2004), "Do Promotions Benefit Manufacturers, Retailers, or Both?" *Management Science*, 50 (May), 617-629.

Van Heerde, Harald J., Marnik. G. Dekimpe, and William P. Putsis, Jr. (2005), "Marketing Models and the Lucas Critique," *Journal of Marketing Research*, February, 42 (1), 15-21.

Villanueva, Julian, Shijin Yoo, and Dominique M. Hanssens (2006), "The Impact of Marketing-Induced vs. Word-of-Mouth Customer Acquisition on Customer Equity," January 2006, working paper.

Whitman, Janet (2006), "Lessons Learned: New Dot-Coms Seek Attention Cheaply," *The Wall Street Journal*, February 13, 2006.

Wikipedia (2006), "List of Social Networking Websites," (accessed May 22, 2006), [available at http://en.wikipedia.org/wiki/List_of_social_networking_websites].