ESTIMATING THE DYNAMIC EFFECTS OF ONLINE WORD-OF-MOUTH ON MEMBER GROWTH OF INTERNET SOCIAL NETWORKS

Michael Trusov, Randolph E. Bucklin, Koen Pauwels[1]

Draft December 16, 2006

Please do not cite or quote without permission of the authors

[1] *Michael Trusov (Michael.Trusov@anderson.ucla.edu) is a doctoral candidate, Randolph E. Bucklin (randy.bucklin@anderson.ucla.edu) is a Professor of Marketing, Anderson School at UCLA, 110 Westwood Plaza, Los Angeles, CA 90095. Koen Pauwels (koen.h.pauwels@dartmouth.edu) is an Associate Professor, Tuck School of Business at Dartmouth, 100 Tuck Hall, Hanover, NH 03755.*

ESTIMATING THE DYNAMIC EFFECTS OF WORD-OF-MOUTH REFERRALS ON MEMBER GROWTH OF INTERNET SOCIAL NETWORKS

ABSTRACT

While several sources tout the superiority of word-of-mouth over traditional marketing communication techniques, it still remains unclear how to measure word-of-mouth and how to compare its relative effectiveness in improving long-term performance. Internet social networking sites offer an attractive opportunity to study word-of-mouth due to their consistent and efficient tracking of electronic referrals. The authors test for and find endogeneity among WOM-referrals, signups, event marketing and media appearances. A Vector Autoregressive (VAR) modeling approach captures this dynamic feedback system and gives estimates for the short-term and long-term effects on signups. The authors find that word-of-mouth benefits carry-over much longer than traditional marketing actions do. The long-run elasticity of signups to WOM appears close to 0.5 – at least 2.5 times larger than average advertising elasticities reported in the literature. For the analyzed firm, 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 contribution of advertising income from a signup, the authors calculate the economic value for a referral, providing an upper bound for financial incentives to stimulate word-of-mouth.

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

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" (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). Indeed, consumer attitudes toward advertising plummeted between September 2002 and June 2004. Forrester (2005) reports 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 compared to other marketing tools in increasing firm performance over time. This raises the need for further study of how firms can best 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 (ibid, e.g.

the Superbowl ads of Careerbuilder.com and GoDaddy.com), it is of broad interest to understand the relative effectiveness of word-of-mouth versus other marketing communication efforts. 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, as the sites provide easy-to-use tools for current users to invite others to join the network. They are also capable to record these activities.

Internet companies commonly employ several types of WOM marketing activities. These include (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 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.[2]

In this paper, we examine one specific form of WOM activity: electronic referrals. Our objective is to estimate the elasticity, both short and long-run, of word-of-mouth referral activity at an Internet social networking site. We compare these elasticity estimates with those obtained for media appearances (public relations) and event

[2] A detailed overview of different forms of WOM marketing is available at the Word of Mouth Marketing Association web site (www.womma.org).

marketing – the main company-sponsored marketing activity. An important aspect of our approach is to 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 empirically test for this endogeneity using Granger causality tests. We then develop a Vector Autoregression (VAR) model to handle endogeneity problem. 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.

Our empirical results from the social networking site show that WOM referrals strongly affect new customer acquisition. 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 (Hanssens et al 2001). For the company under 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 economic implications by calculating how much the average acquired customer contributes to firm revenues. This computation provides an upper limit to the financial incentives the firm could offer existing customers to stimulate word-of-mouth (a practice also growing rapidly in offline use).

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 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. Studying 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. Thus, we 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 marketing-induced customers add more short-term value to the firm, but word-of-mouth customers added nearly twice as much long-term value. However, the authors do not observe the marketing inputs and thus can not directly estimate the response of customer acquisition to WOM and to traditional efforts.

Our paper differs from above studies in research question and application. First, we aim to directly compare the dynamic performance effects of word-of-mouth referrals with that of traditional marketing efforts and quantify the economic value of each WOM referral to the firm. Second, our empirical application is to an Internet social networking site, a novel setting for a marketing study.

Internet social networking sites

While still a relatively new Internet phenomenon, online social networking has already attracted attention from major industry payers. 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 site's provided interface are easily tracked. Some sites offer incentives to make a referral. For example, Netflix.com recently offered its existing customers to pass 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 use 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 to this topic.

Modeling Approach

A typical 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. How should we model the effectiveness of these communication mechanisms? As a base 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, general increases in content and interest in social networking sites. Seasonal patterns may be high (e.g. day-of-week) frequency, as most Internet use occurs during weekdays (Pauwels and Dans 2001) and low frequency, e.g. yearly holiday periods. Equation (1) specifies our base this 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 is the day index, Y_t = signups (new subscriptions), X_t = WOM-referrals, M_t = number of media appearances, E_t = number of promotional events, C = constant, T = deterministic trend, d_i = indicators for days of the week (using Friday as the benchmark), H = holiday dummies (summer break) and J the number of lags of the dependent variable needed to ensure the residuals ε_t are white-noise errors (no residual autocorrelation).

Equation (1) only considers the immediate effects of marketing actions on signups. To include dynamic effects, we can add lags of the marketing actions, thus obtaining an autoregressive-distributed lag (ARDL) model (Hanssens et al. 2001):

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

While model (2) now captures dynamic effects, it does not account for indirect effects of marketing actions on performance. For instance, 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. These asserted links can be tested by investigating which variables Granger cause each other (Granger 1969).

[Figure 2. Modeling Approach]

To capture this dynamic system, we specify and estimate a vector-autoregressive (VAR) model. Compared to alternative specifications, VAR models are especially well suited to measure dynamic interactions between 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 (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:

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

with J = number of lags included (the order of the model), D the vector of day-of-week dummies and ε_t = white-noise disturbances distributed as $N(0, \sum)$.

The vector of endogenous variables Signups (Y), WOM-referrals (X), Media appearances (*M*) and Promotional events (*E*) is related to its own past, allowing 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 (Holidays) dummy variables *H*. Instantaneous effects are captured by the variance-covariance matrix of the residuals $\sum$. In the absence of cointegration, vector autoregressive (VAR) models are estimated with the stationary variables in levels and the evolving variables in differences.

VAR modeling is commonly employed for problems of quantification of short- and long-run market response (Dekimpe and Hanssens 1999). First, the endogenous treatment of WOM implies it also is explained by its own past and the past of the Signups variables. 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. Second, dynamic effects are not *a priori* restricted in time, sign, or magnitude. As for the former, permanent effects are possible for evolving performance variables, and statistical criteria such as Akaike information criterion (AIC) suggest lag lengths J that balance model fit and complexity (Lutkepohl 1993). As for the latter, 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 (Pauwels et al. 2002).

Testing for Evolution or Stationarity: Unit-Root Tests

To determine whether the endogenous variables are stable or evolving, we perform unit root tests. The results of the unit root analyses subsequently affect 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. 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 VARX 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 maintain $|t_{value}| < 1$ to assess whether each impulse-response value is significantly different from zero (this follows the tradition of VAR-research published in marketing journals).

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 combines 36 weeks of daily numbers of signups and referrals (provided to us by the company) with marketing events and media activity (obtained from 3rd party sources). The data covers 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 an increasing 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 cosponsored 101 promotion events. On some days, multiple events occurred in different locations. Overall, 86 days in the observation period had some promotion 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 was 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 rather 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. In sum, we feel the number of media appearances is a useful measure for our research purpose.

Direct effects of marketing on signups

Table 3 displays the results of regressing signups on the marketing actions, either focusing on the immediate effects (equation 1) or adding carry-over effects (equation 2).

[Table 3 Regression analysis results]

Across both 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 a similar effect magnitude, with WOM having 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. In fact, the base model in equation (1) outperforms larger models based on adjusted R^2 and the Akaike information criterion.

Endogeneity (Granger causality test results)

Next, we investigate the endogeneity of the four key variables, by performing Granger causality tests for up to 20 lags. We infer that a variable Granger causes another if at least one test reaches 5% significance. The results are shown in Table 4.

[Table 4 Granger Causality test results]

Endogeneity is clearly present in our data, as Granger causality is detected among almost all pairs of variables. The only exceptions are intuitive: 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 contrast, signups do Granger cause WOM referrals (the “snowball” effect argued earlier), events (indicating management performance feedback, e.g. Dekimpe and Hanssens 1999), and media (indicating that spikes in signups receive media attention). Moreover, events Granger cause media (indicating that media covers events) and media Granger causes events (indicating that management aims to coincide events with pending media coverage). These Granger causality test results 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 sequentially added day of the week effect, and holiday effect. The model fit results are provided in Table 5. The AIC criterion suggests that the best model includes all of the proposed effects. Finally, the AIC criterion indicates 2 as the optimal lag length.

[Table 5 Model Fit Results]

We conclude our estimation by computing the impulse response functions. Figures 5a, 5b and 5c plot the response of signups to a shock in respectively WOM, events and media.

[Figure 5. Impulse Response Functions]

Our analysis shows that it takes approximately three weeks for the IRF of signups to stabilize after a one standard deviation shock on referrals (WOM). Beginning with the 20^{th} period, we observe non-significant effects in the impulse-response function. In contrast, the effects of media and events become insignificant much faster, respectively after 3 and 4 days.

Long-term elasticity of marketing actions

To quantify the long-run elasticity of referrals (and the other marketing actions) on signups, we calculated arc elasticities. We used the following approach. First, from the IRF analysis we calculated the total change in number of signups as a response to one standard deviation shock to WOM-referrals ΔY. Second, using our dataset we calculated the standard deviation for signups (σ_X) and mean values for signups ($\bar{Y}$) and WOM-referrals ($\bar{X}$). Finally, we use equation (4) to calculate arc elasticity η_{arc}.

$$\eta_{arc} = \frac{\Delta Y}{\sigma_X} \times \frac{\bar{X}}{\bar{Y}} \tag{4}$$

This is a standard elasticity formula, except that ΔX is substituted for σ_X, because this is a change in X used to generate IRF. The results of these calculations are displayed in Table 6. That table gives the elasticity at 1 day, 3 days, 7 days and the total long-term elasticity.

The immediate elasticities differ from those obtained by the regression analysis. Media and events have a much higher elasticity, as in the VAR setting their indirect benefits are also accounted for. In contrast, WOM-referrals have a lower elasticity, indicating that some of its estimated effects in the regression analysis were actually initiated by the firm's other marketing actions.

WOM-referrals appear to be the "gift that keeps on giving". Due to the slow decay over time, the 3-day, 7-day and total long-term elasticities are substantially higher than that based on regression analysis. In the long-run, 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 displayed in Figure 2. It is interesting to note that the direct WOM elasticity is close to the average advertising elasticity of 0.1 – 0.2 reported in the literature (Hanssens et al 2001), but that the total long-run elasticity is several times higher. Many previous studies only accounted for direct effects of advertising (e.g. for overview see Bucklin and Gupta 1999), not for indirect benefits such as increasing retailer support (e.g. Reibstein and Farris 1995) and increasing investor awareness (Joshi and Hanssens 2006).

Managerial implications: economic 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. In this section, we conduct a simulation to highlight the economic 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 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 plugging in corresponding 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 unique visitors 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. Finally, using our estimations of long-run marginal effect of WOM, we conclude that each invitation sent is worth about 75 cents per year. Accordingly, by sending out 10 invitations, each network member brings about $7.50 to the firm. The firm's 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 application to online social community site. For the collaborating site we tracked actual outgoing WOM-referrals recorded electronically, matched it with new customer addition 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 (Hanssens et al 2001). In addition, our estimated WOM effect on new customer acquisition is also larger 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 economic 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 per each referral.

Our research also has several limitations. Most importantly, our data come from one social networking site, so 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 reduced form, and thus 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 it's not an "organic" word-of-mouth anymore. Indeed, we might call it "fertilized" word-of-mouth. And in such a case we do not know whether fertilized word-of-mouth would produce the same elasticity as the organic word-of-mouth observed in our data. Especially if the paid nature is known to invitees, fertilized word-of-mouth is likely to be less effective than organic word-of-mouth. In this respect, our economic value calculations may provide an upper bound of the money generated by word-of-mouth. On the other hand, our data may miss some benefits to word-of-mouth; i.e. signups not captured through either the referral process at invitation or the self-report process at signup. Finally, our simulation does not consider other important elements of CLV such as user's impact on retention and site usage of 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. The proposed approach does not allow evaluation of customer value beyond a volume of generated referrals. Therefore, a next step would be to develop an individual level model that allows user-specific contributions to the network.

References

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

Bucklin, Randolph E. and Sunil Gupta (1999), "Commercial Use of UPC Scanner Data: Industry and Academic Perspectives," *Marketing Science*, Vol. 18, No. 3, Special Issue on Managerial Decision Making, 247-273.

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", as appears at http://www.emergencemarketing.com/archives/2006/05/social_networking_sites_d.php, May 22, 2006.

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, W. Lomax and H. Robinson, H. (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.

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

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

Pauwels, Koen H., Imran Currim, Marnik G. Dekimpe, Dominique M. Hanssens, Natalie Mizik, Eric Ghysels and Prasad Naik (2004), "Modeling Marketing Dynamics by Time Series Econometrics," Marketing Letters, 15, 4 (December), 167-183

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," as appears at http://en.wikipedia.org/wiki/List_of_social_networking_websites, May 22, 2006.

Table 1. Social Networking Sites Ranking

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*

	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

*The numbers reported in Table 2 and Figure 3 have been monotonically transformed to preserve the anonymity of the collaborating site. Actual data were used in econometric analysis.

Table 3: Regression analysis explaining log of signups

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

*t-statistic is reported 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

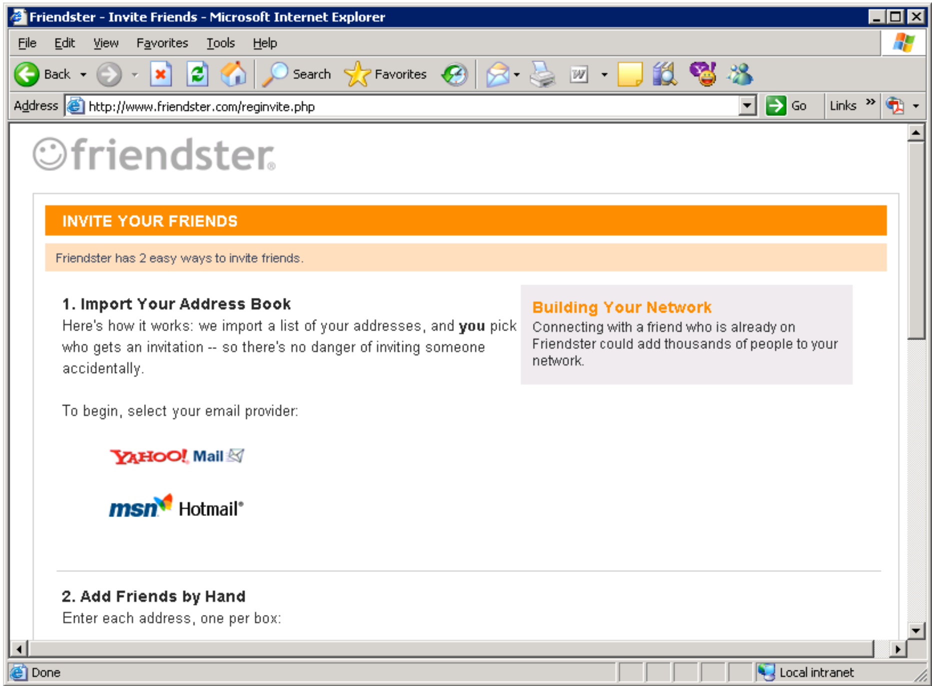

Figure 1b. Referrals Process at Tribe.com

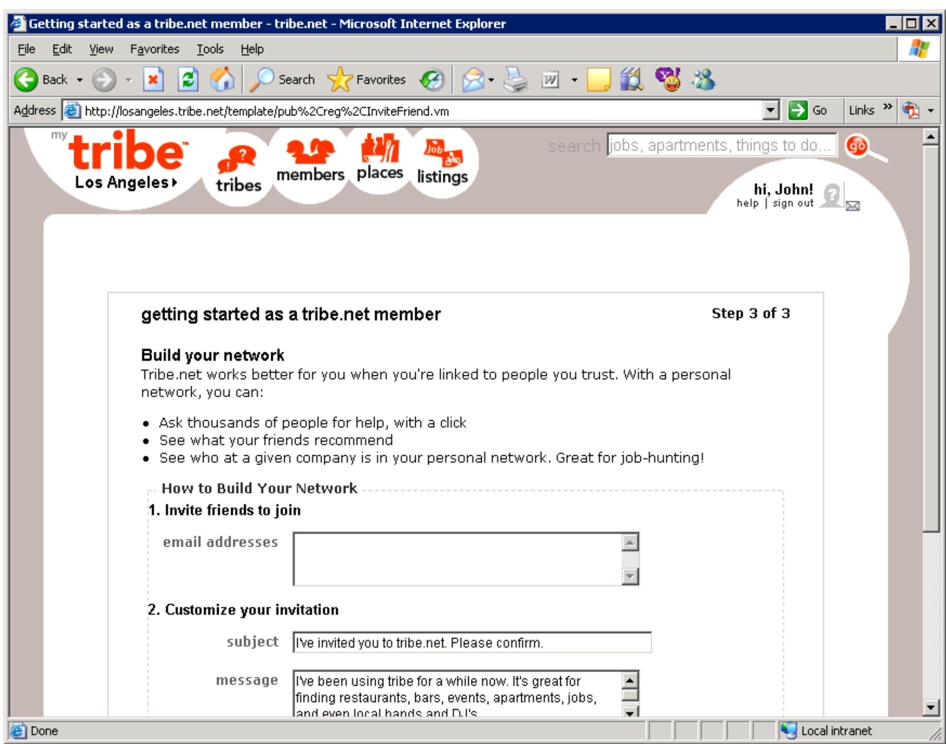

Figure 2. Modeling Approach

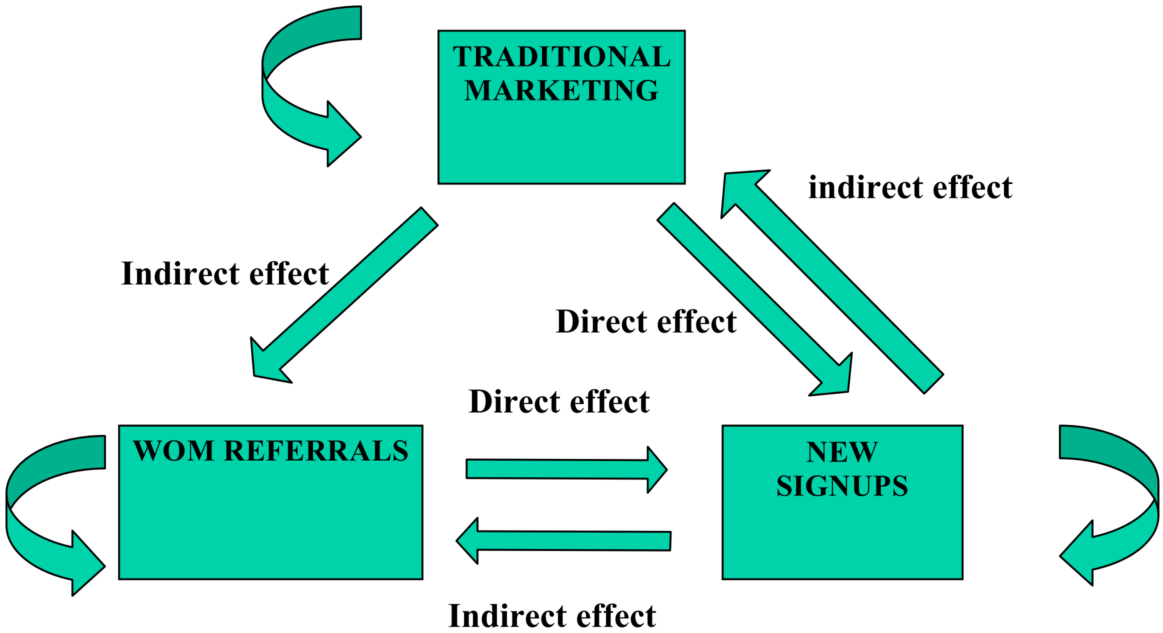

Figure 3a. Time Series: WOM Referrals

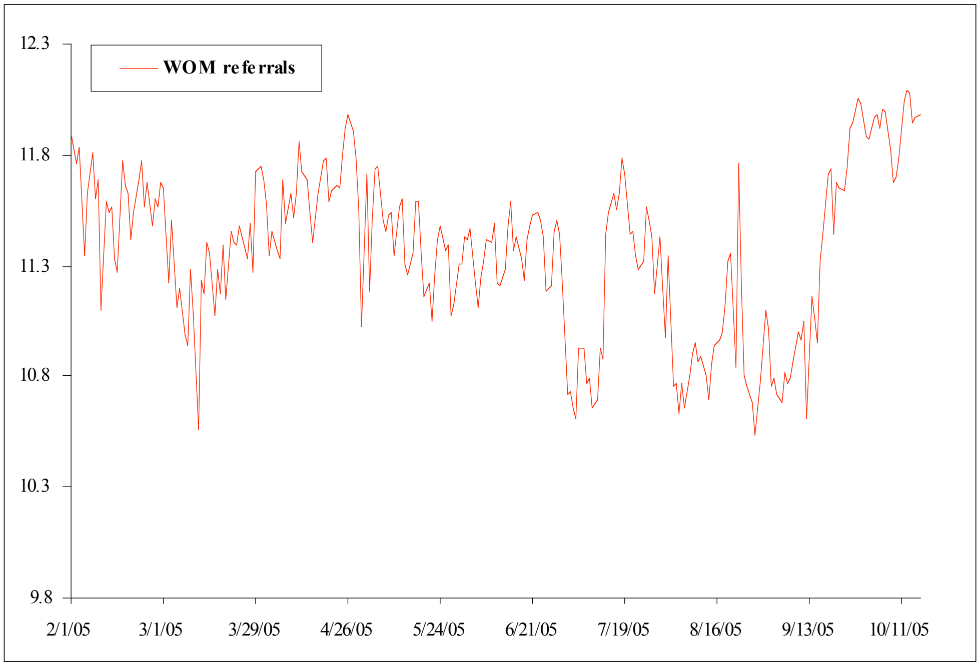

Figure 3b. Time Series: Signups

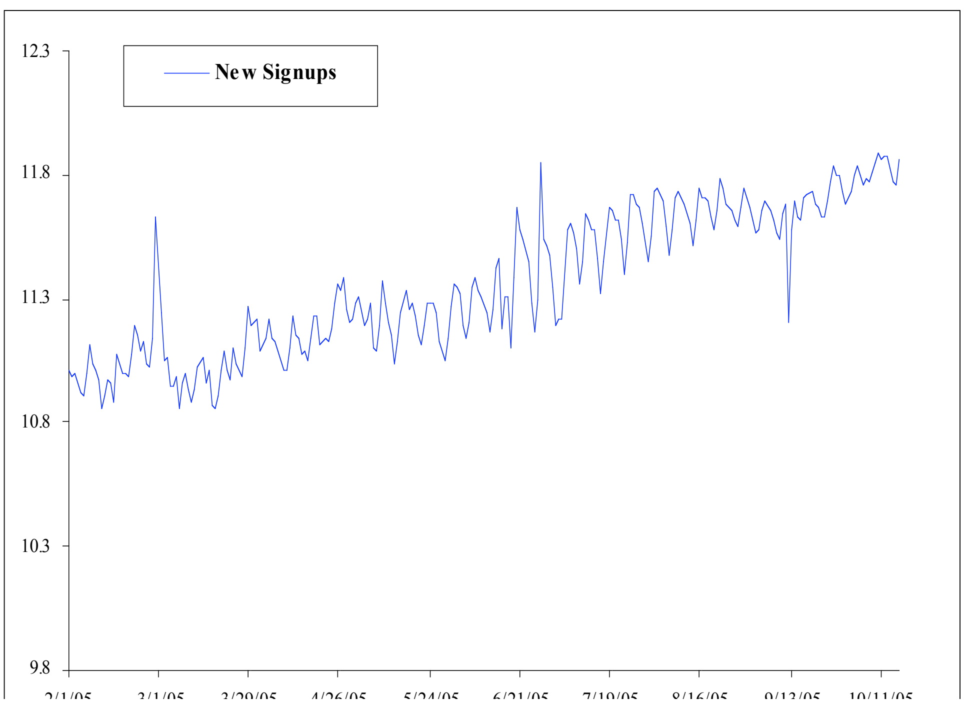

Figure 4a. Time Series: Promotional Events

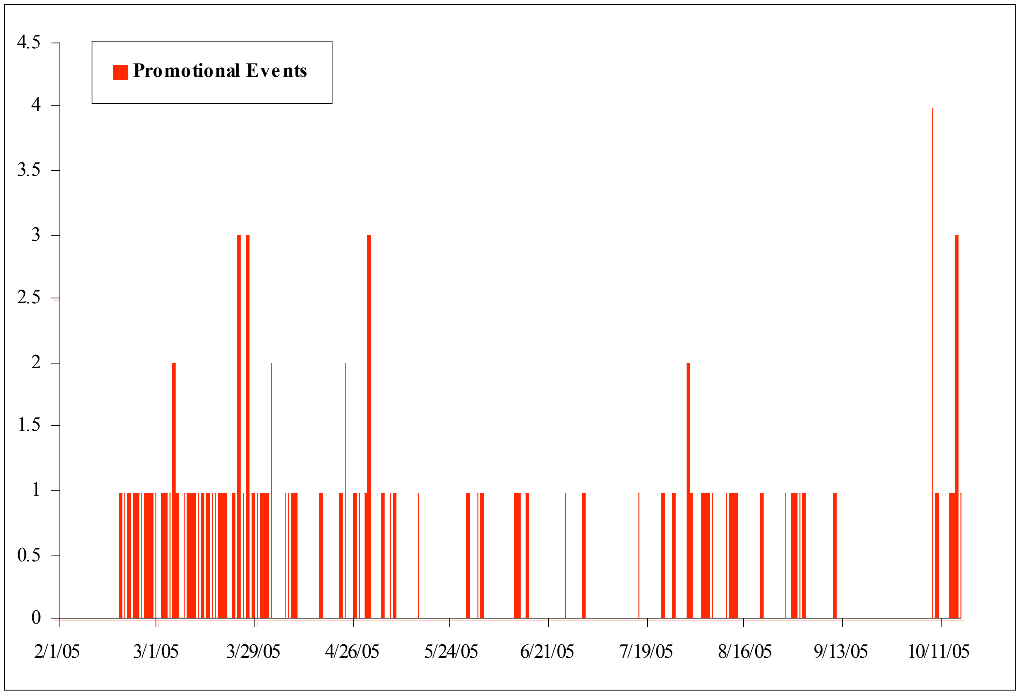

Figure 4b. Time Series: Media Appearances

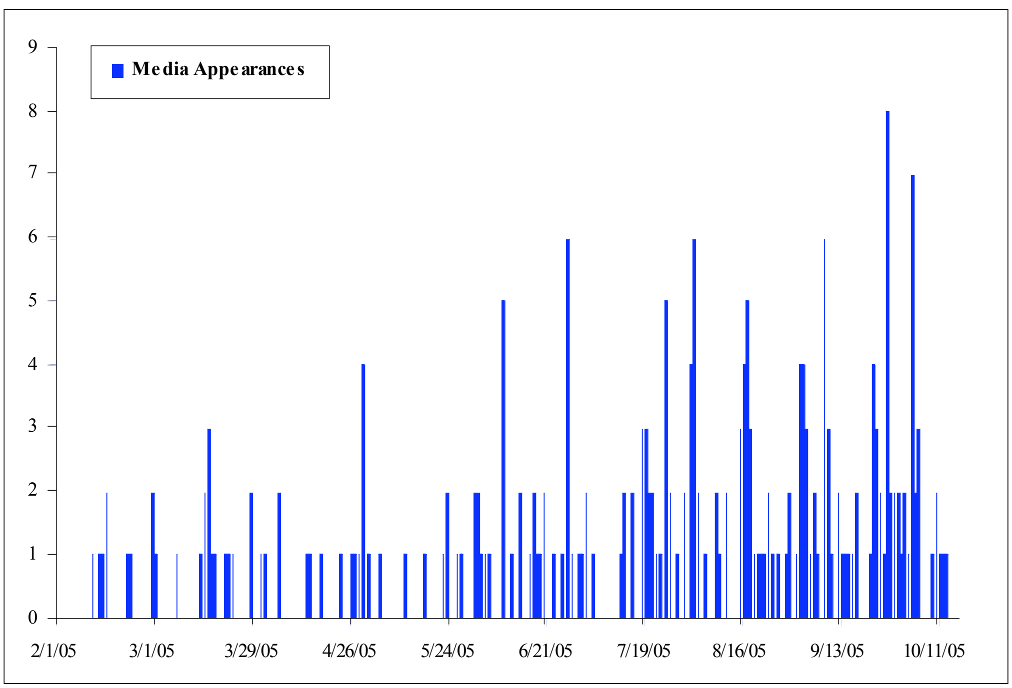

Figure 5a. IRF: Response of Signups to Shock in Referrals

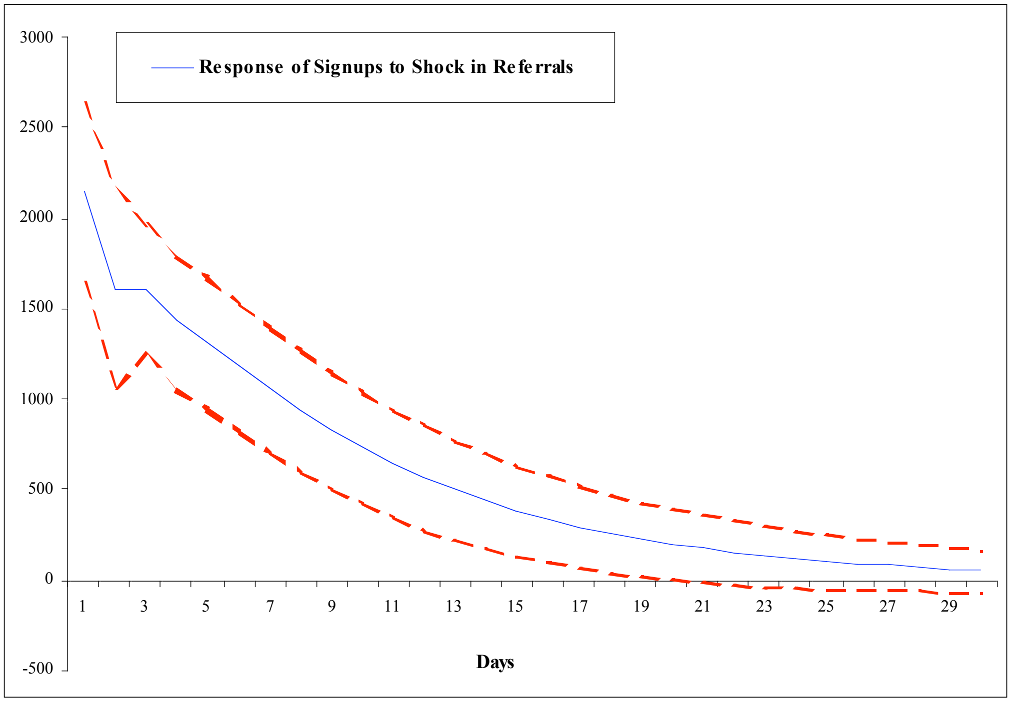

Figure 5b. IRF: Response of Signups to Shock in Media

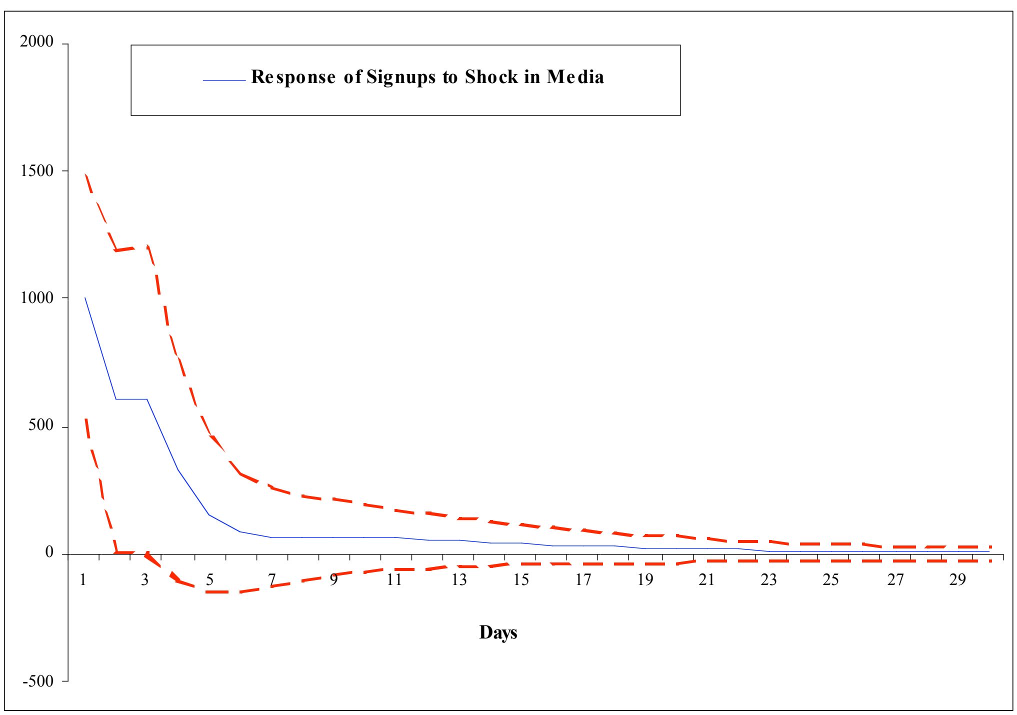

Figure 5c. IRF: Response of Signups to Shock in Promotional Events