Social Advertising: Does Social Influence Work?

Ashish Agarwal
Assistant Professor
McCombs School of Business
University of Texas, Austin
Austin, TX 15213
Phone: (512) 471 5814
Email: ashish.agarwal@mccombs.utexas.edu

Kartik Hosanagar
Associate Professor of Operations and Information Management
The Wharton School
University of Pennsylvania
552 Jon M. Huntsman Hall
3730 Walnut Street
Philadelphia, PA 19104
Phone: (215) 573 0831
Email: kartikh@wharton.upenn.edu

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ABSTRACT

We study the impact of social influence on the performance of ads on social networks. Using data for several ads on Facebook for two different firms, we measure the impact of past connections on the click rate and endorsement rate of ads. We find that increase in the connections does not lead to an increase in the click performance and may even decrease the click performance. We also find that increase in connections can increase the endorsement rate of ads provided that ads have been clicked. However, when the number of connections is very large the connection performance may also reduce.

Our results inform advertisers on how the social influence impacts the performance of their ads and how should they advertise on social platforms such as Facebook. Our results also provide insight into consumer behavior in social networks. Specifically we show that consumers are less likely to be influenced by social connections to click ads. However, if they do click ads they are more likely to endorse ads if more of their connections do.

Keywords: *Social Media, Social Advertising, hierarchical Bayesian estimation, online advertising, online auctions*

Introduction

Social media platforms are gaining popularity among firms due to their potential ability to use social influence as a more effective way to reach out to individuals. Several studies have demonstrated the usefulness of social media in the promotion of products (Aral and Walker, 2011), diffusion of information goods (Susarala et al. 2010; Yoganarasimhan 2012) and diffusion of prescription drugs (Iyengar et al. 2011). Another possible avenue for using social media is brand promotion. Firms can use a social platform to spread information about their activities and promote their brand. Facebook, one of the most popular social platforms, provides such an opportunity to firms using a feature called sponsored stories. Users can endorse firm related activity promoted as a sponsored story by the firm and make a connection with the firm on the Facebook platform using a 'Like'.[1] If a user endorses a firm, other users in their social network can see the endorsement. They, in turn, can evaluate the firm related information by clicking the sponsored story and also endorse the brand by using a 'Like'. A potential benefit of social ads over display ads is that these are targeted at individuals who have already endorsed the ad and likely to have similar preferences. Thus, the performance can be much better as compared to display ads where the target audience is not very well known. Further, if more friends connect with the ad and this social influence leads to higher success for advertisements then advertisers can increase their exposure and increase the number of connections by making higher payment. An important question is whether the social influence plays a role in brand promotion on a social platform such as Facebook. This is important as firms have to evaluate their return from these platforms as compared to other media such as television, print, banner and search ads and have to allocate appropriate budgets to promotions through such platforms. While Facebook generates significant revenue from its sponsored stories[2], current market

[1] http://online.wsj.com/article/PR-CO-20120924-903885.html?mod=crnews

[2] http://techcrunch.com/2012/10/23/facebook-q3-advertising-revenues-up-36-to-1-09b-14-on-mobile/

reaction to Facebook's IPO suggests some skepticism about its long term potential to generate advertising revenue.[3] Advertisers also have shown a mixed response to the performance of ads on Facebook.[4]

The effectiveness of brand promotion would depend on the extent to which users are evaluating brand content endorsed by their social connections and to what extent they are connecting with the brand themselves. In the context of Facebook sponsored stories this can be measured using the click performance as well as the connection performance of a sponsored story. Online banner ads shown on websites have met with limited success as users tend to ignore such ads. Similarly, users on a social platform may not be actively seeking firm or brand related activities when they are using the platform. As a result, they may ignore sponsored stories. However, it is possible that a user may be more willing to click and evaluate a sponsored story as it is endorsed or 'liked' by a friend. However, clicking a sponsored story may or may not result in an endorsement. Only a few studies have evaluated the role social media in brand promotion. Tucker (2012) uses a Facebook ad campaign dataset of a charity firm to show that social ads are more effective than regular ads. She finds that while social influence plays some role, the contribution is primarily due to the ability of ads to target individuals with similar preferences. However, she does not evaluate the role of the magnitude of social signals on the ad performance. Additionally, as Tucker (2012) focuses on a non-profit organization her results could be driven by altruism and may not be very representative. Bakshy et al (2012) find that increase in the number of social cues leads to higher click performance as well as higher endorsement rate of ads on Facebook. However, they restrict their analysis to ads where only a few friends have endorsed the ads. From Advertisers' perspective it does not adequately answer the question as to what extent should they seek endorsements or connections by bidding more.

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3 http://online.wsj.com/article/SB10001424052702303768104577462393468083290.html

4 http://finance.yahoo.com/news/facebook-advertising-ineffective-200916160.html

Addressing this gap, in this paper we seek to analyze if there is social influence on the click performance of sponsored stories? We also evaluate if there is social influence on connection performance conditional on users clicking a sponsored story? We investigate these questions by using a unique panel dataset of sponsored stories performance for two different advertisers on Facebook. Our dataset consists of daily social impressions, clicks and connections for several ads for each of these advertisers. We use a hierarchical Bayesian model to analyze the probabilities for clicking and connecting(i.e. liking) as a function of the number of existing connections. We address endogeneity issues by simultaneously modeling the user decisions, platform decisions and firm's spending decisions.

We find that an increase in the number of connections does not necessarily lead to an increase in the click performance and can result in a decrease in the click performance for a large number of connections. This suggests that users tend to ignore ads if more of their friends are endorsing the ads. We also find that the connection performance conditional on clicking increases with an increase in the number of connections. However, it increases at a decreasing rate with an increase in the connections. This suggests that once users click a sponsored story they are more likely to connect with the brand as more of their friends connect. However, they may stop endorsing it if a large number of their friends are already connected with the advertising firm.

We believe our study makes several contributions. From an advertisers' perspective we answer an important question whether social influence works in promoting their ads. Our research suggests that while social influence works advertisers have to be careful not to overpay to establish connections as connections seem to have diminishing returns. More existing connections can lead to a decrease in click performance as well as connection performance. Our study also suggests that the connection performance maybe different from the click performance and that advertisers should consider both while making their investment decisions. Our study also informs the social media platform on how to promote ads. Our results suggest that the platform should restrict the display of social ads to users once several of their friends have already established connections with the advertiser.

We also contribute to the literature on social media influence. Previous research has demonstrated that social media influence can be used for propagating information as well as promote products. Our research extends this work by evaluating the role of social influence in brand promotion. We show that social influence does play a role in promoting brands through advertisements but only to a limited extent. We also add to the literature on the role of social cues on the social influence. Previous work has suggested that increase in social cues improves the performance (Bakshy et al. 2009, Bakshy et al. 2012). However, our results suggest that if the social cues are very strong then social influence can have a negative effect. Our study also reveals the mechanism through which social influence works in brand promotion in advertisements. We show that that social influence plays a role in both clicking ads and connecting with the brand. While social influence has a negative effect on the clicking of ads it has a positive effect on making connections after clicking. However, this positive effect goes away as more friends make connections with the brand.

Finally, our research makes an important contribution to the literature on social media influence by evaluating the performance of social media from a firm's perspective. Previous work has primarily dealt with the task of establishing social influence as well as investigating the impact of characteristics of the user network on performance. However, these studies have not considered firm decisions such as the extent of promotion on these platforms well as how can this evaluation be made using the data available. Our study sheds light on the extent to which firm's should advertise on a social media platform such as Facebook. We do so using an aggregate dataset which is representative of the information available to advertisers as they engage with consumers through the social media platform. Thus, we also provide an approach to evaluate performance of advertiser campaigns on such platforms.

Literature Review

Our research is most closely related to the literature on social influence and the consumer response to advertising. We review these two streams of literature below.

Social Influence

Researchers studying how social media leads to social influence have mainly focused on the characteristics of the social network . This literature considers the network structure as a whole as well as the characteristics of nodes as well as the connections between the nodes and their impact on the social influence exerted by the network. In this context, researchers have proposed and validated competing hypotheses. One suggests that a structure with weak and sparse connections is more effective in spreading the information as the nodes are transmitting non redundant information in such a structure (Granovettar, 1973). Centola and Macy (2007) find that in complex contagion where there is a need for enforcement the weak ties may not be effect not effective In a setting requiring social reinforcement such as spreading health information such structure is less effective as compared to a lattice structure with redundant connections (Centola et al, 2010). Similarly, strong ties have been linked with higher spread of knowledge and creativity (Sosa, 2011).

Researchers considering the characteristics of the individuals have tried to identify who are the most influential users in a social network. Bakshy, Hoffman, Mason and Watts (2011) establish that the most influential users on Twitter are the ones with the largest number of connections. However, they find that individuals with an ordinary influence maybe most cost effective in spreading influence. Katona et al. (2010) show that the average influence of individuals decreases with an increase in the number of their contacts. Using simulations Watts and Dodds (2007) show that what matters for diffusion of information is that there is a large number of individuals who can be easily influenced or are more susceptible. Aral and Walker (2012) establish the characteristics of the influential and susceptible members on Facebook. Yoganarasimhan (2012) finds that a node with higher number of friends in a social network is more effective in spreading the content. Susarala et al. (2010) find that both the centrality of the node and the number of connections have an impact on the social influence of the node in spreading content on Youtube.

Few researchers have looked at how the intensity of social signals leads to social influence. Katona et al (2011) show that an individual connected to many adopters had a greater adoption probability for a social networking site. Bakshy et al. (2011) find that the adoption rate of assets on second life increases as more friends adopt it. Aral and Walker (2011) find that the while active messages send by social connections are more effective in influencing product adoption by friends, the passive broadcast messaging is overall most effective in spreading the diffusion of products. Bakshy et al (2012) find that increase in the number of social cues leads to higher click performance as well as higher endorsement rate of ads on Facebook. However, they restrict their analysis to users with maximum 3 affiliations. Our research adds to their work in several ways. First of all we consider the cumulative effect of social influence across all users on the performance of ads. We also do not impose any restriction on the number of connections. This allows us to evaluate the impact of social influence on users with large number of connections associated with that particular advertisement. Tucker (2012) uses a Facebook ad campaign dataset of a charity firm to show that social ads are more effective than regular ads. She finds that while social influence plays some role, the contribution is primarily due to the ability of ads to target individuals with similar preferences. However, as Tucker (2012) focuses on a non-profit organization her results could be driven by altruism and may not be very representative. Further, Tucker (2012) does not evaluate the social influence as a function of the number of connections and cannot comment on any non linear social impact of connections.

Ad Persuasion

If a user selects an ad and endorses the firm she is revealing her affinity for the brand. Past research has shown a positive effect of social influence on brand choice (Witt, 1968, Reingen et al, 1984). This would suggest that friends should influence the selection and endorsement of social ads meant for branding purpose. Products consumed in public are those seen by others and are important for identity communication (Childers and Rao 1992). Ratner and Kahn (2002) show that consumers seek greater variety for publicly consumed products. Cheema and Kaikati (2010) show that the need for uniqueness can affect the positive word of mouth for publicly consumed products. Brand endorsement on Facebook is a public knowledge among the peers. If uniqueness plays a role then the social influence can have a negative effect on the individual tendency to click and endorse. A brand endorsement can be viewed as a confirmation of user tastes. Lewis et al. (2011) show that friends in a social network do not influence each other's tastes and preferences. Thus, even if a user decides to click on a sponsored story, she may not like it just because her friend liked it.

Thus, the previous literature suggests that friends can have an influence on the promotion of social ads on Facebook. However, the extent of this influence is not known and is an open and managerially significant question.

Social Advertising on Facebook and Data Description

Facebook allows advertisers to post ads on its network in order to reach out to consumers. Sponsored stories are advertisements that are displayed in the news feed of users along with other news feed related to a user's friends on Facebook. A user sees a sponsored story only if her friend has endorsed it using a 'Like'. Figure 1 shows an example of a sponsored story. These stories are used by advertisers to communicate information about their brand or to promote a new product or spread information about an event. When a user sees an ad, she may choose to ignore the ad or click it. Once, the user clicks the ad she goes to the Facebook page of the advertiser. A user can choose to 'Like' the ad which serves as an endorsement of the Ad. A 'Like' results in a connection with the advertiser. Then, the user directly gets future information feeds from the advertiser. Once, a user has established a connection with the advertiser, her friends become potential candidates for displaying the same ad as a news feed with a cue suggesting that the user has 'liked' the ad.

Advertisers target users based on keywords. These keywords reflect user interest. It is possible that several ads are competing for user attention based on the endorsement of these ads by a user's friends. Facebook uses an auction to prioritize the ads. Advertisers submit bids. Facebook uses bids and the expected click performance of advertiser's to rank these ads. The expected click performance reflects the underlying quality of advertisers to attract user attention. An advertiser can increase its exposure to the Facebook users by submitted higher bids. These would results in more impressions, clicks and ultimately more connections.

Our dataset was provided by a social media marketing firm which manages Face book marketing campaigns for several large firms. It consists of targeting and performance data for a period of 45 days for sponsored stories promoted by two different advertisers: a well known electronics manufacturer and a cruise travel company. Our unit of analysis is a sponsored story ad which is targeted to a specific user population using a set of keywords. Each advertiser runs several sponsored stories. For our analysis, we consider only those ads which get at least 5 connections during the panel period.

Previous work (Granovettar, 1973) has shown that the information contagion is not effective in a closely tied network as the information is redundant. If an ad story is providing lot of information then users may just get the information from the ad after seeing the ad through one connection and may not respond to ads with more connections as they would have already acquired the information. Our sample ads were targeted with an intention of attracting the users to the advertisers' facebook page and did not provide any information upfront in the ad. This would remove the possibility of click behavior getting influenced by the amount of information available in the ads. Additionally, the content was not changed during the panel period.[5]

We evaluate the impact of connections made in the previous period on the click through rate and connection rate in the present period. Lagged connections represent already existing connections. It is possible that connections made in earlier periods may also influence the current performance. However, users associated with past connections would have been already exposed to the ads in the past. As a result, either they are already connected with the advertiser or they do not have any interest in connecting. Thus , the platform is less likely to show ads associated with connections made in the past. It is also possible that some users check their news feeds less frequently and may get influenced by a connection which was

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5 We have separately verified this with the social media marketing firm.

made a few days ago. In order to account for this we also consider the connections made in the past 3 days to represent existing social connections.

Ad performance can depend on the targetability of the ad. We also determine how generic an advertisement is based on the nature of keywords it is targeting. It the ad is targeting a very large population using very generic keywords then we set the generic value to 1. However, if the ad is targeting only specific keywords then we set the generic value to 0. For example, keyword 'travel' is very generic. However, keyword 'Corpus Christi' is very specific. We use Google trends relative search volume index for keywords to determine the popularity of keywords and set the generic value. We take the most popular keyword in our data and label it as generic (generic value of 1). If a keyword's relative search volume is less than half of the search volume of the most popular keyword then we label it as specific (generic value= 0). It is possible that an ad is targeting users based on a combination of generic and specific keywords. In that case we take set the generic level of the ad as the average of the generic level of all the associated keywords.

Our resulting data consists of daily social impressions, clicks and connections for 49 ads over a 45 day period from June 2012 to July 2012 for the cruise travel company. Similarly, we have daily social impressions, clicks and connections for 269 ads over the same period for the electronics manufacturer. Table 1 provides the summary statistics of our final sample for the two advertisers. Note that the observations represent daily aggregate data for advertisements corresponding to the sample ads for our advertisers, and that the dataset is typical of the information received by the Facebook advertisers. We do not have information on the performance of competing advertisements or detailed information on how an individual consumer makes a choice, information that would not typically be available to an advertiser.

Simultaneous Model

Consider an advertiser targeting a set of users for a sponsored story ad based on a certain keywords. Advertiser creates the ad and submits a bid. Face book uses this bid, and the expected ad performance, to determine how often to show the ad. When the eligible users see the ad, some decide to click on the ad, and subsequently connect with the advertiser using a 'Like'. In the process, users can be influenced by the number of friends already connected with theadvertiser. The advertiser's bid decision and Facebook's ranking decision influences the connections made the advertiser. We simultaneously model consumers' click-through and connection behavior, and use an IV approach to address the endogeneity of the connections.

Click through Rate per Impression (CTR)

Social impressions represent the number of times a story was shown using social connections. Higher number of social impressions should result in higher number of clicks as more users are likely to be exposed to the story. Social impressions for a sponsored story also depend on a number of other factors such as the login behavior of individuals, spending budgets of firms as well as the competition among firms to get an impression. Thus, a story may just get more clicks because of these other variables which do not really represent social influence. In order to account for this variance in social impressions, we measure the click performance in terms of the ratio of the number of social clicks and the number of social impressions or the click through rate. This is also the measure used by the platform to evaluate the performance of different firms.

Social influence can be captured by the effect of existing social connections on the click through rate. If users can influence others in their social network to evaluate and endorse the advertiser, then the click through rate should increase with increase in the number of existing social connections. Note that if there is no social influence then the click through rate will not be affected by increase in connections. As we deal with aggregate data we do not have information about the actual number of friends of a user who form connections with the brand. What we have is the total number of connections formed on a daily basis. As the number of connections increase it is more likely that a target user is associated with more connections who have endorsed the advertiser. While all connections can have an influence it is more likely that users associated with the most recent connections are more likely to be influenced. As a result we only consider the most recent connections spread over one to three days to represent the extent of social influence. Further, we classify connections into 4 distinct categories to represent different scale of connections achieved. The purpose, of doing so is the capture any non linearity in the response of performance to connections. We take the log value of actual lagged connections and divided it in equal parts to determine these categories. Our baseline category is the one with the lowest number of connections.

Click performance varies across ads. This depends on the ad characteristics. We use ad keywords to capture the ad characteristics. Keywords represent the target audience for ads. As described earlier, we use the popularity of keywords to determine the generic level of each ad. Click performance of an ad can be influenced by unobserved characteristics of the ad. For example, some ad may be targeted at a group of users who are more likely to click and endorse the ad as compared to users for other ads. We account for the impact of these unobservable characteristics using a random effects approach. We use a hierarchical model to capture the effect of ad characteristics. This provides a flexible random component specification that allows us to incorporate both observable and unobservable ad-specific heterogeneity, given the small number of connections for each ad. Hierarchical models are commonly used to draw inferences on individual level characteristics (e.g., Rossi and Allenby, 2003). HB models have also recently been applied to study sponsored search data with keywords as a unit of analysis (Ghose and Yang 2009; Yang and Ghose 2010; Agarwal, Hosanagar, and Smith 2011).

We assume an i.i.d. extreme value distribution of the error term for individual choices and use a logit model to represent the click probability for an ad a at time t as follows

(1) $$\Lambda_{a,t}^{CTR} = \frac{exp\,(U_{at}^{CTR})}{1+exp\,(U_{at}^{CTR})}$$

where U_{at}^{CTR} is the latent utility of clicking. For ad a at time t, the latent utility of clicking can be expressed as

(2)

$$U_{at}^{CTR} = \theta_0^a + \theta_1^a LConnections1_{at} + \theta_2^a LConnections2_{at} + \theta_3^a LConnections3_{at} + \ \theta_t Time_{at} + \varepsilon_{at}^{\theta}$$

$$\theta^a = \Delta^{\theta} z_a + u_a^{\theta} \qquad u_a^{\theta} \sim N(0, V^{\theta})$$

where

LConnections1, LConnections2, LConnections3 are dummies representing different categories of lagged connections (LConnections1< LConnections2< LConnections3 based on the number of connections)

Time controls for time dynamics in the auction,

$\varepsilon_{at}^{\theta}$ represents the time varying unobserved keyword attributes that are common for all consumers,

z_a represents keyword specific characteristics: brand and specificity. Δ^{θ} is a matrix capturing the relationship between keyword characteristics and the mean values of coefficients,

and u_a^{θ} represents the unobservable heterogeneity for each keyword, which we assume is normally distributed with a mean 0 and covariance matrix V^{θ}

Connection Rate per Click (CONR)

On clicking an ad a user may evaluate the associated Facebook page and elect to endorse the advertiser using a 'Like'. As mentioned before, clicks can be driven by several factors not related to social influence and these in turn can influence the social connections. So we define the connection performance as the ratio of the number of connections to the number of clicks or the connection rate. Once again the number of existing social connections would proxy the extent of social influence.

Connection rate (probability) refers to the fraction of clicks that generate connections. Assuming an i.i.d. extreme value distribution of the error term for individual choices, we can express the connection probability as

(3)
$$\Lambda_{at}^{CONR} = \frac{exp(U_{at}^{CONR})}{1+exp(U_{at}^{CONR})}$$

where U_{at}^{CONR} is the latent utility of conversion. For ad *a* at time t, this latent utility can be expressed as

(4)

$$U_{at}^{CONR} = \beta_0^a + \beta_1^a LConnections1_{at} + \beta_2^a LConnections2_{at} + \beta_3^a LConnections3_{at} + \beta_t Time_{at} + \varepsilon_{at}^{\beta}$$

$$\beta^a = \Delta^{\beta} z_a + u_a^{\beta} \qquad u_a^{\beta} \sim N(0, V^{\beta})$$

Endogeneity of Existing Social Connections

Existing social connections represent the extent of social influence. However, existing connections could be correlated with firm specific promotions which are outside the platform. A firm may be willing to spend more on the social platform while running these promotions. This in turn could be driving the click and connection performance. The social platform can also strategically decide to promote only certain firms by showing their ads to the users in response to some external event. In that case, the existing social connections can be correlated with these unobservable time varying attributes which could also be driving the click and connection performance. In order to correct for the resulting bias, we have to account for the firm's spending choices as well as the platform's choice to show a firm's ad.

Facebook uses a firm's bid and its expected click performance to rank it among firms targeting the same group of individuals. A firm can get more impressions and as a result more clicks and connections by submitting higher bids. Thus, existing connections are a function of firm's bid. Bid information is not available to us. We use the cost per click incurred by the firm as a proxy for a firm's bid. As the firm increases the bid for its ad, it can expect to improve its ranking among competing ads and get priority in displaying the ad in the news feed. However, this is accompanied by an increase in the cost per click. Lagged connections for a story *a* at time *t* can be expressed as

(5) $LConnections_{at} = \alpha_0^a + \alpha_1 LCPC_{at} + \varepsilon_{at}^{\alpha}$

$with\ \alpha_0^a = \Delta^{\alpha} z_a + u_a^{\alpha}\ and\ u_a^{\alpha} \sim N(0, V^{\alpha})$

where $LCPC_{a,t}$ is the lagged cost per click for story *a* at time *t*. The random coefficient accounts for the unobservable quality of the ad.

A frm's bid for an ad will be correlated with its bids for other ads. If two ads target different groups of individuals then the valuation of these ads will be independent. However, the bids for these ads would be correlated due to common cost factors. As a result we use lagged CPC of other non related stories i.e. stories targeting different set of individuals as an instrument for the lagged CPC of a sponsored story.This is similar to the approach adopted by Hausmann et al. (1996), Nevo (2001) and more recently Ghose, Ipeirotis, and Li (2012) to use prices of the product in other markets as an instrument.

Lagged CPC for a story *a* at time t can be expressed as

$$(6)\ LCPC_{at} = \gamma_0^a + \gamma_1 OtherCPC_{at} + \gamma_{Time} Time_{at} + \varepsilon_{at}^{\gamma}$$

$$with\ \gamma^a = \Delta^{\gamma} z_a + u_a^{\gamma}\ and\ u_a^{\gamma} \sim N(0, V^{\gamma})$$

Finally, as the lagged connections (LConnections) as well as the lagged CPC (LCPC) are endogenous, the unobservable time varying keyword attributes for the equations representing consumer decisions will be correlated with error terms for the equations representing LConnections and LCPC. As such, we use the following distribution to account for correlation between the error terms:

$$(7)\qquad \begin{bmatrix} \varepsilon_{at}^{\beta} \\ \varepsilon_{at}^{\theta} \\ \varepsilon_{at}^{\alpha} \\ \varepsilon_{at}^{\gamma} \end{bmatrix} \sim N(0, \Omega) \text{ where } \Omega = \begin{bmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} & \Omega_{14} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} & \Omega_{24} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & \Omega_{34} \\ \Omega_{41} & \Omega_{42} & \Omega_{43} & \Omega_{44} \end{bmatrix}$$

Identification

The above set of simultaneous equations represent a triangular system, which has been addressed by authors in classical (Lahiri and Schmidt 1978, Hausman 1975, Greene 1999) and Bayesian econometrics (Zellner 1962). It can be represented as follows:

$$\mathrm{U}_{\mathrm{at}}^{\mathrm{CTR}} = \mathrm{f}(\mathrm{LConnections}, \varepsilon_{\mathrm{at}}^{\theta})$$

$$\mathrm{U}_{\mathrm{at}}^{\mathrm{CONR}} = \mathrm{f}(\mathrm{LConnections}, \varepsilon_{\mathrm{at}}^{\beta})$$

$$\mathrm{LConnections} = \mathrm{f}(\mathrm{LCPC}, \varepsilon_{\mathrm{at}}^{\gamma})$$

$$\mathrm{LCPC} = \mathrm{f}(\mathrm{X4}, \varepsilon_{\mathrm{at}}^{\alpha})$$

In this setup, LConnections and LCPC are endogenous, while the variable X4 is exogenous. Identification arises from the fact that LCPC is determined by the exogenous variable: OtherCPC. As noted above, LCPC is correlated with OtherCPC due to common cost components. LCPC determines LConnections which in turn influence click and conversion performance.

Thus the rank and order conditions are satisfied for identification purposes (Greene, 1999). Lahiri and Schmidt (1978) have shown that the parameter estimates for a triangular system can be fully identified using Generalized Least Squares. Hausman (1975) shows that the likelihood function for a triangular system is the same as for Seemingly Unrelated Regressions. Zellner (1962) has addressed triangular systems from a Bayesian point of view, and shows that the posterior probability distribution function is the same as in a Seemingly Unrelated Regressions setting. Triangular systems have been estimated using the classical approach (Elberse and Eliashberg 2003; Godes and Mayzlin 2004) and more recently in sponsored search using the Bayesian approach (Ghose and Yang 2009; Yang and Ghose 2010; Agarwal, Hosanagar and Smith 2011).

We estimate the model using a Bayesian approach, applying Markov Chain Monte Carlo sampling due to the non-linear characteristics of our model (Rossi and Allenby 2005). A more detailed discussion of the priors and conditional posteriors of this model is given in Online Appendix. For the HB Models, we run the MCMC simulation for 80,000 draws and discard the first 40,000 as burn-in. In order to ensure that our parameter estimates are accurate we have simulated the clicks, connections, and LCPC values using our estimates. By repeating the estimation with this simulated dataset we were able to recover our parameter estimates, indicating that our parameters are fully identified.

Results

Click through rate (CTR)

Table 2 provides the mean values for the posterior distribution of the Δ^{θ} matrix from equation 2 for both our advertisers. The coefficient for the lagged connections does not change across categories for the electronics manufacturer. When we consider one day lag for existing connections the coefficient is insignificant for all categories. For the three day lag the coefficient is positive and significant for all three categories. However, it is not changing across categories even though the number of connections is increasing. Thus, the click performance is not changing with increase in the number of connections.

For the cruise travel company, the coefficient is negative and significant for all the categories for both one day lag period and three day lag period. This suggests that the click performance is actually decreasing with the increase in the number of connections for the cruise travel company.

One possible reason for decrease in the click performance with connections is that users may seek uniqueness in their affiliation for brand. Consumers tend to diverge from others while buying products if the products signal their identity (Berger and Chip, 2007). Same mechanism maybe playing a role when users connect with advertisers through sponsored stories. Their connection or endorsement is known to their friends. As a consequence, if many friends connect with the same advertiser, the user maybe less inclined to do so.

Connection rate (CONR)

Table 3 provides the mean values for the posterior distribution of the Δ^{β} matrix in equation 4. The coefficient of LConnections is positive and significant for all categories for both advertisers. This suggests that the connections have a positive effect on the connection performance conditional on clicking. Also, the coefficient is increasing as we move to the higher category of connections. This suggests that the increase in connections does lead to an increase in the connection rate. However, the coefficient is increasing at a decreasing rate. Our categories are based on the log values of connections. This indicates that connections in category LConnections3 are much higher in magnitude as compared to connections in category LConnections2. Thus, the connection rate may be actually decreasing for very high number of connections. This is especially true for generic ads which tend to get higher click performance for the lower category of connections (Table 3). This again suggests that users tend to not connect if a large number of their friends are already connected with the advertiser.

Connection rate shows better response to existing connections as compared to the click rate. This suggests that users who have decided to click are more likely to respond to social influence. Thus, our results also reveal how users respond differently to the social influence depending on their action.

LCPC and LConnections

Table 4 provides the mean values for the coefficient of the LCPC which is the instrument for LConnections. As expected, the coefficient for LCPC is positive and significant. As the advertiser is willing to spend more per click, it can expect to get more impressions and more connections. Table 5 provides the mean values for the posterior distribution of the Δ^{α} matrix and V^{α} from equation 6. In these results, higher other CPC values lead to higher focal LCPC. This is reasonable as we expected higher spending of the advertiser to be correlated across ads.

Finally, Table 6 shows the covariance between unobservables for CTR, CONR, LConnections, and LCPC from equation 7. Covariance between the unobservables for CONR and CTR is statistically significant. This indicates that the unknown factors influencing consumer clicks also influence subsequent connection behavior. These error terms are also directly or indirectly correlated with unobservables for LConnections and LCPC . This suggests that the unobservables influencing LConnections and LCPC are also influencing CTR and CONR, meaning that LConnections and LCPC are endogenous and the proposed simultaneous equation model helps to capture the effect of this endogeneity.

Discussion and Conclusion

Practitioners are trying to determine the potential of social media platforms such as Facebook for promoting their brand. Facebook offers one such option in form of ads called 'Sponsored Stories' which only appear in the news feed of users who have friends already connected with the advertiser. As more friends connect with the advertiser the social signal gets stronger. Very few studies have evaluated the performance of social ads and none have systematically evaluated the role of existing connections on the performance of ads. In our research we analyze how existing connections influence the performance of social ads on Facebook.

To do this, we use a unique dataset consisting of sponsored story ad campaign for two different advertisers on Facebook. In this dataset we have the daily social impressions, clicks, and connections as well as cost per click for several ads associated with these two advertisers.. We analyze our data using a hierarchical Bayesian model, and accounting for the endogeneity of the existing connections. Our results show that an increase in the existing connections may not influence the click performance or even hurt the click performance. We also find that an increase in the existing connections improves the connection rate. However, for a large no of connections this performance goes down.

These results are important for several reasons. From a practitioner perspective, our results emphasize the importance of analyzing the impact of existing connections on their performance. A selling point for using social media platform is that the advertising can be more targeted due to similarity of preferences of individuals in a network as well as the possibility of social influence to improve performance. Our results suggest that impact of the social influence maybe limited. Our findings suggest that advertisers should not spent too much to build connections as these can hurt the ad performance. Facebook should restrict the sponsored stories to a few individuals in a network to improve the effectiveness of social influence. Also, Facebook should recognize that connection performance may not mirror click performance, and thus clickthrough rates alone may not be sufficient as performance measures for ads.

Finally, our results inform the academic literature regarding consumer behavior in these environments.. In our data, click-through rate is not influenced or negatively influenced by increase in existing social connections, whereas connection rate is more positively influenced by the existing connections. This suggests that consumers may resist the notion of connecting with a firm and endorsing it if a large number of their friends are already connected. They do so by choosing not to click an ad. However, the ones that do click the ad are more likely to be influenced by the existing connections.

As with any empirical analysis there are several limitations of our study. While, our results explain behavior of consumers at an aggregate level, the aggregate nature of our data limits our ability to account for the actions of individual consumers. This calls for future research using click stream data to empirically evaluate the behavior of different types of consumers in these environments. We also rely on lagged connections to rely on the social influence. This leaves out the impact of connections that have been formed on the same day. This can impact our results if the connections formed on the same day tend to be more influential. In our analysis we do not find significant difference in the influence if we consider different time lags. However, future studies should investigate whether the social influence changes with time. In our study we consider only one type of sponsored story ad. Future studies should investigate different types of ads and the role of social influence on the performance of different ad formats.

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Table 1: Social Ads Performance Summary Statistics

	Electronics Manufacturer				Cruise Travel Company			
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
CTR (Social Clicks/Social Impressions)	0.003	0.03	0	1	0.0004	0.003	0	0.25
CONR (Connections / Social Clicks)	0.34	0.42	0	1	0.3	0.39	0	1.17
Connections (t=t-1)	36.9	127.3	0	1100	5.9	25.14	0	519
Connections (t=t-3 to t-1)	107.1	356	0	3145	17.3	69.1	0	1411
Generic	0.89	0.164	0.19	1	0.72	0.3	0	1
CPC	0.178	0.2	0	0.63	0.41	0.5	0	2.24
OtherCPC	0.362	0.09	0.17	0.51	0.94	0.12	0.75	1.18

Table 2: Estimates for the CTR

Electronics Manufacturer

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	-7.574 (0.115)***	0.396 (0.192)**	-7.602 (0.105)***	0.295 (0.276)
LConnections 1	-0.068 (0.068)	-0.114 (0.305)	0.207 (0.065)***	-0.118 (0.361)
LConnections 2	-0.071 (0.057)	-0.107 (0.214)	0.279 (0.077)***	0.126 (0.294)
LConnections 3	-0.091 (0.075)	-0.213 (0.24)	0.26 (0.088)***	-0.259 (0.273)

Cruise Travel Company

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	-7.978 (0.332)***	-0.206 (0.436)	-8.344 (0.282)	-0.309 (0.415)
LConnections 1	-0.474 (0.17)***	0.469 (0.602)	-0.465 (0.211)**	0.83 (0.552)
LConnections 2	-0.486 (0.138)***	0.637 (0.447)	-0.399 (0.209)*	0.346 (0.472)
LConnections 3	-0.428 (0.15)***	0.448 (0.396)	-0.407 (0.196)**	0.514 (0.421)

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 3: Estimates for the CONR

Electronics Manufacturer

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	1.548 (0.22)***	-0.692 (0.307)**	1.155 (0.165)***	-0.328 (0.299)
LConnections 1	0.099 (0.089)	1.763 (0.472)***	0.784 (0.095)***	1.107 (0.365)***
LConnections 2	0.292 (0.072)***	0.827 (0.294)***	0.925 (0.073)***	0.196 (0.333)
LConnections 3	0.389 (0.101)***	0.411 (0.296)	1.013 (0.082)***	0.273 (0.336)

Cruise Travel Company

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	1.548 (0.22)***	-0.692 (0.307)**	1.155 (0.165)***	-0.328 (0.299)
LConnections 1	0.099 (0.089)	1.763 (0.472)***	0.784 (0.095)***	1.107 (0.365)***
LConnections 2	0.292 (0.072)***	0.827 (0.294)***	0.925 (0.073)***	0.196 (0.333)
LConnections 3	0.389 (0.101)***	0.411 (0.296)	1.013 (0.082)***	0.273 (0.336)

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 4: Estimates for LConnections

Electronics Manufacturer

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	-0.152 (0.051)***	-0.157 (0.208)	-0.152 (0.063)**	-0.509 (0.285)
CPC	0.156 (0.051)***		0.141 (0.064)**	

Cruise Travel Company

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	1.32 (0.102)***	0.01 (0.226)	1.74 (0.11)***	0.042 (0.229)
CPC	0.506 (0.096)***		0.527 (0.101)***	

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 5: Estimates for LCPC

Electronics Manufacturer

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	0.19 (0.048)***	-0.053 (0.273)	0.189 (0.05)***	-0.049 (0.272)
OtherCPC	0.391 (0.052)***		0.393 (0.053)***	

Cruise Travel Company

	Lagged Connections (t-1)		Lagged Connections (t-1 to t-3)	
	Intercept	**Generic**	**Intercept**	**Generic**
Constant	0.432 (0.071)***	-0.018 (0.21)	0.423 (0.07)***	-0.022 (0.203)
OtherCPC	0.296 (0.031)***		0.305 (0.032)***	

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 6: Estimates for the Covariance Matrix Ω

Electronics Manufacturer

Lagged Connections (t-1)				
	CTR	CONR	LCPC	LConnections
CTR	0.376 (0.025)***	0.059 (0.009)***	-0.065 (0.014)***	-0.011 (0.006)
CONR		0.105 (0.006)***	-0.036 (0.008)***	-0.002 (0.003)
LCPC			0.178 (0.003)***	-0.023 (0.007)**
LConnections				0.047 (0.002)***
Lagged Connections (t-1 to t-3)				
CTR	0.308 (0.012)***	0.033 (0.006)***	-0.011 (0.002)***	0.041 (0.008)***
CONR		0.099 (0.004)***	-0.004 (0.001)***	0.017 (0.005)**
LCPC			0.029 (0.)***	-0.003 (0.001)**
LConnections				0.081 (0.001)***

Cruise Travel Company

Lagged Connections (t-1)				
	CTR	CONR	LCPC	LConnections
CTR	0.413 (0.026)***	0.05 (0.012)***	-0.001 (0.003)	0.003 (0.012)
CONR		0.159 (0.011***)	-0.003 (0.001)**	0.013 (0.008)
LCPC			0.011 (0.)***	-0.002 (0.001)**
LConnections				0.068 (0.002)***
Lagged Connections (t-1 to t-3)				
CTR	0.35 (0.03)***	0.04 (0.013)**	-0.002 (0.002)	0.028 (0.009)**
CONR		0.158 (0.011)***	-0.004 (0.001)***	0.013 (0.007)
LCPC			0.011 (0.)***	-0.003 (0.001)**
LConnections				0.07 (0.002)***

Figure 1: Sponsored Story Ad Example