VIRAL MARKETING: A LARGE-SCALE FIELD EXPERIMENT

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Viral Marketing: a Large-Scale Field Experiment

Abstract

We report the results of a large-scale field experiment performed in the context of the national launch of a new cosmetic product. The manufacturer launched this new product using three promotional tools in parallel: full-page advertisements in fashion magazines, free standing inserts (FSI) in Sunday newspapers, and a viral marketing campaign. Each promotional tool featured an identical discount coupon for the new product, but with different redemption codes across promotional tools. Our data enable us to address the following research questions: (1) How does the effectiveness of viral marketing compare to that of traditional media? (2) What is the relation between online and offline social interactions in viral marketing campaigns? And (3) what characterizes the most active members in a viral marketing campaign? We find that (1) viral marketing compares very favorably to print advertising and FSI, based on the partial but objective measure of coupon redemption rate; (2) although viral marketing campaigns involve a strong online component, most social interactions happen offline and offline social interactions do not substitute online social interactions; (3) a set of simple measures of members' social characteristics may be used to predict word-of-mouth transmission and identify the most active members in a campaign.

1. INTRODUCTION

Viral marketing has become an increasingly popular promotional tool (Kirsner 2005; Walker 2004). According to a 2009 study by the media research firm PQ Media, spending on word-of-mouth (WOM) marketing rose at a compound annual growth rate of 53.7% from 2001 to 2008—from US$76 million to US$1,543 million—and is forecast to reach over US$3 billion annually by 2013 (PQ Media 2009). However, in a 2007 survey of marketing and advertising professionals by Dynamic Logic, half the respondents rated viral marketing as more of a fad than a mainstream and widely available tactic (Dynamic Logic 2007). One of the challenges faced by the viral marketing industry is the lack of formal quantitative and qualitative comparisons of this new promotional tool to traditional tools, and the scarcity of systematic methods for optimizing viral marketing campaigns. If, as recent forecasts imply, viral and WOM marketing become an increasingly common part of the marketing mix, then these kinds of challenges need to be addressed. This paper attempts to offer one small step in that direction.

We refer to viral marketing (also sometimes called word-of-mouth marketing) as a set of promotional tools whereby companies seed products with select groups of consumers in the hope that they will spread WOM about these products, and in turn increase awareness and sales. Firms offering such services include BzzAgent™ (www.bzzagent.com), SheSpeaks™ (www.shespeaks.com), and two Procter and Gamble firms, Tremor (www.tremor.com) and Vocalpoint (site.vocalpoint.com). Each of these firms have built online panels of consumers who are (i) offered early access to new products (e.g., by being sent free samples), (ii) encouraged to share their opinions on these products with other consumers (i.e., transmitting WOM), (iii) asked to participate in surveys to provide feedback on the products to marketers, and (iv) asked to report their WOM-transmitting activities to the firm on a regular basis.

Recently, academic researchers have started to examine viral marketing as a new tool for marketing communications and promotion. Godes and Mayzlin (2009) use a large-scale field test to study how characteristics of WOM transmitters and their recipients (specifically, whether transmitters are loyal or less loyal customers of a restaurant, and whether recipients are their friends or acquaintances) are related to the effectiveness of WOM in a viral marketing campaign. De Bruyn and Lilien (2008) develop a model to identify the role that WOM plays during each stage of a viral marketing recipient's decision-making process. Biyalogorsky, Gerstner and Libai (2001) study customer referral programs theoretically and identify conditions under which they should be used. Van der Lans, van Bruggen, Eliashberg and Wierenga (2009) propose a branching model for predicting the spread of online WOM. Iyengar, Van den Bulte and Valente (2009) study how the degree to which a customer influences other customers varies with his or her position in the social network.

However, little is still known about the effectiveness of viral marketing as a promotional tool compared to traditional alternatives, the types of social interactions on which viral marketing relies, and the identity of the most active members in viral marketing campaigns. The present paper focuses on these issues. In particular, we use a large-scale field experiment conducted in collaboration with a viral marketing firm and a cosmetics company to address the following research questions: (1) how does the effectiveness of viral marketing compare to that of traditional media? (2) What is the relation between online and offline social interactions in viral marketing campaigns? And

(3) what characterizes the most active members in a viral marketing campaign? We further address our third research question with additional data from another campaign conducted later by the same viral marketing firm for a packaged food product. This additional dataset allows us not only to test the robustness of our findings, but also to assess whether the most active members in a viral marketing campaign may be identified *before* the start of the campaign.

The paper is organized as follows. We detail our research questions and review the relevant literature in Section 2. We describe the design of our experiment in Section 3, and the results in Section 4. We conclude in Section 5.

2. RESEARCH QUESTIONS AND RELEVANT LITERATURE

We discuss each of our three research questions in turn.

2.1 Effectiveness of Viral Marketing versus Other Promotional Tools

To the best of our knowledge, our first research question has not yet been addressed empirically. Given that WOM can have positive effects on aggregate marketing outcomes (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004), viral campaigns that are aimed at generating WOM and spreading it between consumers should at least have the potential to be effective promotional tools. However, their effectiveness has not been compared to other (so-called traditional) forms of marketing communications. Our field experiment was conducted in the context of the national launch of a new nail polish product that used three communications tools in parallel: magazine advertisements, free standing inserts (FSI) in newspapers, and viral marketing. In each case, coupons offering a $1 discount on the purchase of the new product were offered. The coupons were identical across promotional tools, but with different redemption codes, thus enabling us to compare redemption rates across the three tools as an aggregate outcome-based measure of campaign effectiveness.

2.2 Relation between Online and Offline Social Interactions

We address our second and third research questions using data collected from the members of the viral marketing campaign. Our second research question responds to Godes et al.'s (2005) call for research on understanding the relationship between online and offline social interactions. Although most viral marketing firms use sophisticated Internet-based platforms to run their campaigns and to encourage (and track) the diffusion of online WOM, offline WOM (either in person or via other means, such as telephone conversations) likely occurs. The interplay between online and offline WOM in viral campaigns, however, is not well understood.

2.3 Campaign Member Characteristics that Predict Word-of-Mouth Transmission

Our third research question has both theoretical and practical relevance. Theoretically, it is not yet fully understood *what types* of consumers are the greatest *creators* of WOM in viral marketing campaigns. Practically, being able to identify the most active members before the start of a campaign would make it possible to optimize the sample of members recruited for the campaign (i.e., seed selection).

We assess how well a set of social member characteristics predict the level of WOM transmission during a viral campaign. It is reasonable to argue that the identity of the most active members in a campaign may also vary based upon their tastes and consumption habits. Therefore, we contrast these social characteristics, which do not depend on the specific product being advertised in the campaign, with a set of variables that capture members' attitudes towards the specific category, brand and product under consideration (see Table 1). Whether product-related member characteristics are required to identify the most active members has important managerial implications as it affects managers' ability to identify and solicit a set of active "agents" before the start of a campaign.

[INSERT TABLE 1 ABOUT HERE]

We focus on three main social characteristics, which are grounded in previous research. The first two items measure the social connectivity of the member, and the third measures the perceived impact of his or her recommendations.

The first two items, which capture the number of social connections a member has and how "social" he or she is, were part of the "network breadth" scale proposed in an earlier version of Godes and Mayzlin (2009).[1] Godes and Mayzlin found some preliminary yet inconclusive evidence that members who score high on that scale are more active in viral campaigns. The rationale behind these items is that, all else equal, the number of social interactions about a specific product is increasing in the overall total number of social interactions in which a member typically engages, and how generally "social" that person is. Some justification for this argument may be traced back to Coleman, Katz, and Menzel (1957), who showed that physicians with high connectivity in their social networks play a critical role in diffusion (although this finding has been

[1] This scale is not mentioned in the final published version of Godes and Mayzlin (2009).

brought into question by Van den Bulte and Lilien 2001). Similarly, Iyengar, Van den Bulte and Valente (2009), in their study of the diffusion of a new prescription drug among physicians, find that a physician with a larger in-degree centrality (e.g., number of other physicians who nominated that physician as someone with whom they felt comfortable discussing the clinical management and treatment of the disease) has a greater impact on the adoption of other physicians. Finally, Goldenberg, Han, Lehmann, and Hong (2009) empirically show that individuals who are highly central in a social network (i.e., have a large number of connections) are critical for accelerating the diffusion of innovation over this network.

The third social characteristic that we consider captures the perceived effect of these social interactions on recipients' behaviors ("When you recommend products or services to friends, what do they usually do?"). The rationale behind this item is that consumers who believe that their recommendations have more impact should be more likely to engage in WOM. Indeed, Stephen and Lehmann (2009) show experimentally that transmitters of WOM take into account how likely a given recipient is to listen to them before deciding whether or not to share product-related information with that person.

Note that our measures do not include the standard opinion leadership scale (e.g., Rogers and Cartano 1962; King and Summers 1970). The role of this scale in viral marketing was studied by Godes and Mayzlin (2009). Their field experiment involved a set of "agents" from BzzAgent (a viral marketing firm), and a set of customers enrolled in the company's loyalty program. They found that while opinion leadership had an impact of WOM activity among members of the company's loyalty program (referred to as "customers"), it had no impact among the BzzAgents (referred to as "noncustomers").

3. EXPERIMENTAL DESIGN AND DATA COLLECTION

We worked in collaboration with OPI, a leading manufacturer of cosmetic products, in the Spring/Summer of 2008 as the company was launching a new product, Nic's Sticks. Nic's Sticks are innovative nail polish pens designed for easy and quick application. The polish is applied using a brush at one extremity of the pen. A clickable pump at the other extremity allows the user to control the flow of polish. See Figure 1 for a picture of the product.

[INSERT FIGURE 1 ABOUT HERE]

OPI launched this new product using three promotional tools in parallel. The first two involved print media advertising, and the third was a viral marketing campaign:

- *Full page advertisement in a fashion magazine*. This magazine had a circulation of approximately 2.5 million copies and a target audience similar to the new product's target audience. These advertisements contained a manufacturer's coupon for $1 off the purchase of the new product. See Figure 1 for a picture of the coupon;
- *Free Standing Inserts (FSI) in Sunday newspapers*. A total of approximately 2 million inserts were distributed. These inserts contained some promotional material on the new product, as well as the same coupon for $1 off the purchase of the new product;
- *Viral marketing campaign*. OPI and SheSpeaks™ ran a viral campaign involving 4,315 members of the SheSpeaks™ panel. This viral campaign

> followed the typical steps of a viral marketing campaign. First, members of the panel were invited to participate by email. Second, members filled out an "enrollment" survey that assessed their initial dispositions towards nail polish (category), OPI (brand), and Nic's Sticks (product). While such surveys are typically used to screen members (e.g., for seed selection), we did not screen members in our experiment in order to increase variety in our sample. Third, members received a package by mail containing a free sample of the Nic's Sticks nail polish product, five coupons (see Figure 1), and a double-sided postcard introducing the product and the campaign. Fourth, a few weeks later, members were invited by email to fill out an optional "evaluation" survey, asking for their post-usage evaluation of the product, and asking them to report their WOM transmission activities during the campaign. We describe both the enrollment and evaluation surveys in more detail below.

It is important to note that while we were fortunate to influence the design of a major national product launch campaign and turn it into a field experiment, we were limited in the number of experimental factors that we were able to vary. Accordingly, our experiment is not a full factorial experiment, but rather a comparison of *best practices* in viral marketing to *best practices* in magazine advertising and *best practices* in FSI advertising. The design of the experiment does not allow us to understand the source of the differences between conditions, i.e., these differences may not be attributed to any single factor on which these promotional tools differ. In particular, the following factors were varied simultaneously across conditions. First, members of the viral marketing campaign were given five coupons and a free sample each while only one coupon and no free sample were included in each magazine advertisement and FSI. The distribution of free samples and multiple coupons is the norm in viral marketing, while single coupons are more typical in magazine advertising and FSI. Second, the promotional material was different across conditions. However, one may argue that the simple postcard distributed in the viral marketing campaign was visually less sophisticated and appealing than the magazine advertisement. Third, while participants in the viral marketing campaign were a self-selected group that signed up to be part of the panel and of this campaign in particular, the consumers reached by the other two promotional tools were simply readers of the magazine and newspapers in which the product was advertised. This difference is inherent to the different tools: it would be impossible, for example, to run a magazine advertisement for which readers would have to sign up.

4. RESULTS

We structure the presentation of our results according to our three research questions.

4.1 Effectiveness of Viral Marketing versus Other Promotional Tools

The coupons within each promotional tool had a different barcode number, thus allowing us to track coupons separately for each tool. This offered a unique opportunity to compare viral marketing to traditional media on an objectively quantifiable metric, coupon redemption rate.

The redemption rates, as measured by OPI, were as follows: 0.9% of all coupons distributed in magazines were redeemed, 0.7% of all coupons distributed in FSIs were redeemed, and 12% of all coupons distributed during the SheSpeaks™ campaign were redeemed. The ratio of redemption rates provides very strong support for the effectiveness of viral marketing, at least on this particular metric.

It is important to note a few caveats to this comparison. First, the total number of coupons from magazines and FSIs that were redeemed was obviously larger because of the substantially larger distribution of these channels (i.e., millions of magazines and newspapers circulated versus thousands of members in the viral campaign). Moreover, the cost per coupon distributed was different across the three promotional tools. However, measures of return on investment (the details of which are confidential) also provide strong support for the viral marketing campaign versus the other tools. Second, coupon redemption rate is not the only metric to assess the effectiveness of a promotional tool. For instance, a common goal of magazine advertising is to raise brand or product awareness, and not necessarily to induce action (e.g., purchasing). When measuring the success of a promotional campaign, there exists a tradeoff between using metrics that are well-defined and measurable but only partial, versus metrics that are more extensive but harder to define and measure. In this paper we use a metric of the former type. We hope that our experiment will inspire other studies in other product categories, involving different sets of promotional tools, and using other success metrics. The present study presents only one data point, and claims of generalizability should be avoided.

4.2 Relation between Online and Offline Social Interactions

We now turn to our second research question, which concerns the relation between online and offline social interactions (SI). Our analysis is based on the evaluation survey, which was completed towards the end of the campaign by 1,181 members of the SheSpeaks™ panel who participated in the campaign. We focus on the following two survey items:

- "How much did you talk about the product online (email, instant messaging, chat boards, etc.) versus offline (in person, on the phone, etc.)?"; and,
- "Specifically, how did you communicate with others about Nic's Sticks? [Check all that apply.]".

The first item used an 11-point response scale (0 = "All was online," 5 = "About half was online, half was offline," 10 = "All was offline," and an additional option of "I haven't talked about Nic's Sticks online or offline."). The second item offered a list of 12 non-exhaustive, non-mutually-exclusive methods of online and offline communication with others about the product. This list is reported in Table 2.

[INSERT TABLE 2 ABOUT HERE]

We removed from the analysis the members who selected "I haven't talked about Nic's Sticks online or offline" in the first item, resulting in 1,128 observations. Of all the members, 90.87% gave an answer to the first item that was to the right of the scale's midpoint, indicating that the majority of their social interactions happened offline. This result, while potentially counterintuitive, is consistent with a report from the Keller Fay Group that 90% of WOM takes place offline (Keller and Fay 2009).

The second item helps us to further explore the relation between online and offline SI. Table 2 reports the proportion of respondents who reported using each type of SI, and confirms that offline SI are more prevalent than online SI. While 97.1% of the respondents reported engaging in at least one type of offline SI, only 55.0% reported engaging in at least one type of online SI ($\chi^2(1) = 467$, $p < .001$). Moreover, for 93.71% of the respondents, the proportion of offline SI types selected (i.e., number of types of offline SI selected divided by five) was strictly larger than the proportion of online types selected (i.e., number of types of online SI divided by seven) ($\chi^2(1) = 862$, $p < .001$).

This raises the question of whether offline SI and online SI are used by different types of consumers, and in particular whether consumers who engage in online SI are different from consumers who engage in offline SI. Our data suggest that this is not the case. The correlation between the number of offline types of SI used and the number of online types of SI used was fairly high (.43, $t = 15.9$, $p < .01$). Members who reported engaging in at least one type of online SI also engaged in a significantly larger number of offline types of SI compared to members who reported not engaging in any online SI ($M_{\text{offline|online} = 0} = 2.04$ vs. $M_{\text{offline|online} > 0} = 2.83$; $F(1, 1126) = 132.25$, $p < .01$). More precisely, for all seven types of online SI, the average number of types of offline SI used by members who engaged in that particular type of online SI was at least 23% larger than the average number of types of offline SI used by members who did not engage in that type of online SI (all p-values < .01).

Therefore, our data suggest that although viral marketing campaigns are primarily run from online platforms, offline SI are still predominant, and have not been replaced by online SI. Moreover, consumers who engage more in online SI tend to engage more in offline SI as well.

4.3 Campaign Member Characteristics that Predict Word-of-Mouth Transmission

We now turn to our third research question, the identification of the most active members in the campaign. In particular, we assess how well the social member characteristics introduced in the previous section (and listed in Table 1) predict WOM transmission. We contrast these social characteristics, which are independent of the specific product advertised in the campaign, to product-specific characteristics, which capture a member's attitudes towards the product category, the brand and the product advertised in the campaign.

4.3.1 Data. Our data have four components. These data are collected for every SheSpeaks™ campaign, and similar data are collected by other viral marketing firms (see for example Godes and Mayzlin 2009). First, we obtained data on social characteristics from a survey filled out by members when they joined the panel (i.e., before participating in their first campaign). These data are described in the top half of Table 1. Second, we obtained product-related member characteristics from the enrollment survey, filled out by members at the beginning of the campaign (but before receiving the product sample, information card, and coupons in the mail). These data are described in the bottom half of Table 1. Third, WOM transmission was measured by the number of coupons shared with others (i.e., used to buy a product for others or given to others), which was measured in the evaluation survey along with the number of coupons used by each member to buy the product for herself.[2] Fourth, we obtained demographic data (age and employment status) from the survey filled out by members when they joined the panel. Age was measured using seven categories: below 24, 25-29, 30-34, 35-39, 40-45, 45-49, 50 or above. Employment status was measured with a binary variable indicating whether the member was employed full-time. Our analysis is based on the sample of members for whom all data were available, resulting in 1,032 complete observations.

Because coupons could be shared with others or could be used by members to buy products for themselves, we need to consider and model these two outcome measures.

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[2] We removed from the analysis any member who claimed to have used more than five coupons, since only five coupons were sent to each member.

Our dependent variable is a two-dimensional vector composed, for each member, of the number of coupons used by that member to buy the product for herself and the number of coupons shared by that member with others. Each dimension of this dependent variable is discrete, and the sum of the two dimensions is constrained between 0 and 5. Traditional regression techniques thus do not apply. Instead, we developed the following multinomial logit model which accounts for the discrete choices made and for the tradeoffs between using coupons for oneself versus sharing them with others.

4.3.2 Model Specification. Let $n_{self,i}$ and $n_{others,i}$ be the number of coupons used by member i for herself and shared with others, respectively. Member i makes a choice among 21 possible combinations of coupon usage $\{n_{self}, n_{others}\}$ such that $n_{self} + n_{others} \leq 5$. Let $\mathbf{X}_i$ be a row vector containing a set of covariates describing member i (demographic, social, and product-related characteristics or any subset of these variables). Let $\boldsymbol{\beta}_{self}$ and $\boldsymbol{\beta}_{others}$ be vectors (which we estimate) that capture how these characteristics influence the utility from using one coupon for oneself and from sharing one coupon with others, respectively (each vector includes an intercept, identified because of the possibility of not using any coupon). We model the utility derived by member i from using $n_{self,i}$ coupons for herself and from sharing $n_{others,i}$ with others as:

$u_i(n_{self,i}, n_{others,i}) = [u_{self,i}(n_{self,i}) - c_{self,i}(n_{self,i})] + [u_{others,i}(n_{others,i}) - c_{others,i}(n_{others,i})]$, where the total utility is comprised of the self-usage utility ($u_{self,i}(n_{self,i})$) minus corresponding costs ($c_{self,i}(n_{self,i})$), plus the utility from sharing with others ($u_{others,i}(n_{others,i})$) minus corresponding costs ($c_{others,i}(n_{others,i})$). These costs can be thought of as transaction costs.

The four utility components are specified as follows:

$$u_{self,i}(n_{self,i}) = \begin{cases} 0 & \text{if } n_{self,i} = 0 \\ (\sum_{j=1}^{n_{self,i}} \gamma_{self}^{j-1}) \cdot (\mathbf{X}_i \cdot \boldsymbol{\beta}_{self}) & \text{if } n_{self,i} > 0 \end{cases} \tag{1}$$

$$c_{self,i}(n_{self,i}) = \begin{cases} 0 & \text{if } n_{self,i} = 0 \\ (\sum_{j=1}^{n_{self,i}} \lambda_{self}^{j-1}) \cdot \theta_{self} & \text{if } n_{self,i} > 0 \end{cases} \tag{2}$$

$$u_{others,i}(n_{others,i}) = \begin{cases} 0 & \text{if } n_{others,i} = 0 \\ (\sum_{j=1}^{n_{others,i}} \gamma_{others}^{j-1}) \cdot (\mathbf{X}_i \cdot \boldsymbol{\beta}_{others}) & \text{if } n_{others,i} > 0 \end{cases} \tag{3}$$

$$c_{others,i}(n_{others,i}) = \begin{cases} 0 & \text{if } n_{others,i} = 0 \\ (\sum_{j=1}^{n_{others,i}} \lambda_{others}^{j-1}) \cdot \theta_{others} & \text{if } n_{others,i} > 0 \end{cases} \tag{4}$$

In this specification, $\mathbf{X}_i.\boldsymbol{\beta}_{self}$ and $\mathbf{X}_i.\boldsymbol{\beta}_{others}$ are the utilities derived respectively from using one coupon for oneself and from sharing one coupon with others, and $\gamma_{self}>0$ and $\gamma_{others}>0$ are discount parameters for the marginal utilities derived from additional coupons (i.e., allowing for diminishing marginal utility from coupon usage). For example, $\gamma_{self}^{j-1} \cdot (\mathbf{X}_i \cdot \boldsymbol{\beta}_{self})$ is the marginal utility from the j^{th} coupon used for oneself. The (positive) parameters θ_{self} and θ_{others} are the transaction costs for using one coupon for oneself and for sharing one coupon with others, respectively. The positive parameters λ_{self} and λ_{others} are discount parameters for the marginal costs of using additional coupons. Therefore our model captures diminishing marginal utilities and costs as more coupons are used, with the discount parameters varying between utilities and costs, and between self-usage and sharing.

We write the probability of the dependent variable for member *i* having a value $\{n_{self,i}, n_{others,i}\}$ as the following multinomial logit probability:

$$\Pr(\{n_{self,i}, n_{others,i}\}) = \frac{\exp\left[u_i(\{n_{self,i}, n_{others,i}\})\right]}{\sum_{\{n_{self}, n_{others}\} | n_{self} + n_{others} \le 5} \exp\left[u_i(\{n_{self}, n_{others}\})\right]} \tag{5}$$

We estimate the parameters $\boldsymbol{\beta}_{self}$, $\boldsymbol{\beta}_{others}$, γ_{self}, γ_{others}, λ_{self}, λ_{others}, θ_{self}, and θ_{others} using maximum likelihood. The likelihood function is $L = \prod_{i=1}^{N} \Pr(\{n_{self,i}, n_{others,i}\})$.

4.3.3 Model Comparison and Fit. The covariates that describe member *i* are seven demographic covariates (six dummy variables for age, and one for employment status), six product-related covariates, and eight social covariates. We compare four models, which use four different combinations of these covariates. Table 3 lists the specifications of each of these models and reports fit statistics for each one. Model 1 (demographic covariates only) and Model 2 (demographic and product-related covariates) do not fit as well as Model 3 (demographic and social covariates) and Model 4 (demographic, product-related, and social covariates). Based on AIC, Model 4 (the full model) is slightly superior to Model 3, though by only a small margin.

[INSERT TABLE 3 ABOUT HERE]

4.3.4 Findings. Parameter estimates for the full model (Model 4 in Table 3) are reported in Table 4. The utility and cost discount parameters and unit cost parameters are reported in Table 5. Parameter estimates for the other models are reported in the Appendix.

[INSERT TABLES 4 AND 5 ABOUT HERE]

The analysis of the parameter estimates is not straightforward, for at least two reasons. First, both sets of parameters $\boldsymbol{\beta}_{self}$ and $\boldsymbol{\beta}_{others}$ influence both the number of coupons used for oneself and the number of coupons shared with others, through the constraint that the sum of these numbers is bounded by 5. For example, a positive coefficient in $\boldsymbol{\beta}_{others}$ does not necessarily always imply that a member with the corresponding characteristic will share more coupons with others. In particular, if that covariate has an even greater positive weight in $\boldsymbol{\beta}_{self}$, the reverse may be true. Second, $\boldsymbol{\beta}_{self}$ and $\boldsymbol{\beta}_{others}$ in the model only capture the utility from one coupon. The choice of the total number of coupons used for oneself and shared with others also depends on the discounting parameters and the cost parameters, γ_{self}, γ_{others}, λ_{self}, λ_{others}, θ_{self}, and θ_{others}.

Therefore, while we report the parameter estimates for completeness in Tables 4 and 5, we interpret these parameters using a more intuitive measure focused on our third research question. In particular, we assess how well various sets of covariates are able to identify the most active members in the campaign. We assess the impact of social member characteristics by computing a social score for each member, $score_i^{social} = \mathbf{X}_i^{social}.\boldsymbol{\beta}_{others}$, where $\mathbf{X}_i^{social}$ is the vector $\mathbf{X}_i$ in which all covariates are set to 0 except for the covariates that capture the social characteristics. We then group members into four quartiles according to $score_i^{social}$ and compute the average number of coupons shared with others by each quartile. As the score increases (i.e., going from quartile 1 to 2, 2 to 3, and 3 to 4), the number of coupons shared with others should also increase if the information on which that score is based is informative. We repeat this analysis for the product-related characteristics (i.e., $score_i^{product} = \mathbf{X}_i^{product}.\boldsymbol{\beta}_{others}$), as well as for the whole set of covariates (i.e., $score_i^{all} = \mathbf{X}_i.\boldsymbol{\beta}_{others}$). Our analysis is based on the full model, Model 4. In Table 6, we report the average number of coupons shared with others by each of the quartiles.

[INSERT TABLE 6 ABOUT HERE]

This analysis suggests that members' social characteristics—which are not campaign-specific—are enough to identify the most active members in the campaign, and that campaign-specific, product-related characteristics do not add much information.[3] In particular, the average number of coupons shared by members in the top quartile is 3.64 when the quartiles are based on all covariates, and it is 3.72 when the quartiles are based on members' social characteristics only. This number drops to 3.24 when the quartiles are based only on product-related member characteristics. It is also interesting to note the difference between the number of coupons shared by the top and the bottom quartiles in Table 6. The average number of coupons shared by the top quartile is 60% greater than that shared by the bottom quartile when the quartiles are based on the social member characteristics only. This proportion goes down to 52% and 28% when the quartiles are based respectively on the full set of covariates and the product-related covariates only. Finally, for each set of covariates we compare the average number of coupons shared by members in the top quartile with the average number of coupons shared by all other members (quartiles 1 to 3). The top quartile is significantly more active than the rest when quartiles are based on all covariates ($F(1, 1028) = 47.84$, $p < .001$) or on social member characteristics only ($F(1, 1028) = 35.51$, $p < .001$), but not when quartiles are based on product-related member characteristics only ($F(1, 1028) = .05$, $p = .82$). This analysis is based on the full model, Model 4. We repeat it with Model 2 and Model 3 and obtain similar results (see Table 7).

[INSERT TABLE 7 ABOUT HERE]

4.3.5 Replication and Identification of the Most Active Members Before the Start of a Campaign. In order to test the robustness of our findings, and to assess whether campaign-independent social characteristics may be used to identify the most active

[3] Social characteristics may also be measured in a campaign-specific way; e.g., by asking members how many people they talk to on a daily basis about a specific product category. We leave the exploration of such measures to future research.

members in a campaign *before* the start of a campaign, we used an additional dataset from another campaign conducted by SheSpeaks™. This campaign was for a packaged food product, and ran several months after the OPI campaign.[4] We refer to the OPI campaign as Campaign 1 and to the new campaign as Campaign 2. We obtained complete data for 1,597 members of the SheSpeaks™ panel who participated in Campaign 2. Data are available for both campaigns for only 71 members, therefore there is only very little overlap in our data between participants from both campaigns.

We first replicate the above quartile-based analysis (based on Model 4 – results from the other models are available from the authors). See the first three columns in Table 8. The findings from Campaign 1 are replicated, although the range in the average number of coupons shared by the various quartiles is not as large as in Campaign 1. The average number of coupons shared by members in the top quartile is 3.76, 3.76, and 3.65 when the quartiles are based on all covariates, social member characteristics only, and product-related member characteristics only respectively, and the number of coupons shared by the top quartile is respectively 21%, 20%, and 7% greater than that shared by the bottom quartile. The average number of coupons shared by members in the top quartile is significantly larger than the average number shared by the other members when quartiles are based on all covariates ($F(1, 1593) = 19.77$, $p < .001$) or on social member characteristics only ($F(1, 1593) = 17.39$, $p < .001$), but not when they are based on product-related member characteristics only ($F(1, 1593) = .16$, $p = .69$).

[INSERT TABLE 8 ABOUT HERE]

Beyond replicating the results from Campaign 1, Campaign 2 also allows us to

[4] The details of this other campaign are confidential.

test whether the social characteristics measured when members join the panel may predict the most active members in Campaign 2 *before* Campaign 2 starts, i.e., without using any data from Campaign 2. We compute a social score for each Campaign 2 member using the estimates of $\boldsymbol{\beta}_{others}$ from Campaign 1. This score does not use any data from Campaign 2, as the member social characteristics are measured when members join the panel and the parameter estimates are based on Campaign 1. We report the results in the last column of Table 8. We see that our ability to identify the most active members using social covariates only is equally good when no data from Campaign 2 are used. The average number of coupons shared by members in the top quartile based on Campaign 1 estimates is 3.75, and it is 16% larger than the number corresponding to the 1st quartile. Also, the average number of coupons shared by members in the top quartile is again significantly larger than the average number of coupons shared by the other members ($F(1, 1593) = 17.25$, $p < .001$). Note that the *out-of-sample* predictive ability of member social characteristics is greater than the *in-sample* predictive ability of product-related member characteristics, i.e., member social characteristics combined with parameter estimates from a previous campaign are more informative than campaign-specific product-related member characteristics combined with data from the target campaign.

To summarize, the results of our analysis suggest that a simple set of members' social characteristics may be used to identify the most active members in a campaign. This has important implications for arguably the most critical stage of viral campaigns—the selection of members to be involved in the campaign. Our findings suggest that social characteristics, which are often measured at the time a person joins a panel and which are not campaign-specific, appear to be sufficient to select members of a panel who are likely to be highly active WOM transmitters. Campaign-specific characteristics that measure members' attitudes towards the category, brand and product advertised in the campaign do not appear to add much information. Theoretically, our results suggest that individuals' social interactivity traits are good predictors of their WOM transmission behaviors. Further, attitudes toward specific product categories, brands or products do not appear to have much impact on WOM transmission above and beyond social characteristics.

5. CONCLUSIONS

In relation to our three research questions, our field experiment, combined with data from an additional viral marketing campaign, generated three main findings.

First, our results provide some support for the effectiveness of viral marketing as a promotional tool. Specifically, we found that coupon redemption rates were dramatically higher for the viral campaign than for print advertisements. Print advertisements might serve other purposes than inducing consumers to purchase a product (e.g., raise awareness for a brand or product), and we do not claim that such tools are *generally* ineffective when compared to viral marketing (or word-of-mouth marketing) campaigns.

Second, we found that although viral marketing campaigns have strong online components and are typically run from online platforms, most social interactions still take place offline. Moreover, online social interactions appear as an extension to, and not a substitute for, offline social interactions in these campaigns.

Third, a simple set of member social characteristics—which are not campaign-specific—appear to be good predictors of WOM transmission activity. Product-related member characteristics—which are obviously specific to a given campaign—are not as informative. This suggests that the most active members in a campaign may be identified before the start of the campaign, without using any product-related data.

Our research is not without limitations. First, while our data did come from a field experiment, we did not have complete control over this experiment's design. Thus, our experiment was not a perfectly controlled, full factorial experiment. Second, the data used to address our second and third research questions is self-reported survey data. Coupons were not individually tracked in this campaign, and therefore it was impossible to obtain individual-level redemption data without relying on self-reports. Data on social characteristics and product-related characteristics were also self-reported and therefore subject to the same caveats. While self-reported data has some shortcomings, it is commonly used in the viral marketing industry (see also Godes and Mayzlin 2009) and our approach is at least consistent with standard industry practice. Future research may explore other sources of data on social characteristics (e.g., number of Facebook friends or Twitter followers). Third, our findings come from two viral marketing campaigns. We make no claims of generalizability, and we encourage future research that addresses similar and related questions.

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FIGURE 1

PRODUCT AND COUPON USED IN FIELD EXPERIMENT

TABLE 1

MEASURED SOCIAL AND PRODUCT-RELATED MEMBER CHARACTERISTICS

Question	Response Menu
Social Characteristics	
"About how many people do you talk to on a daily basis?"	1-9 10-19 20-29 30+
"Which best describes you socially?"	Independent: mostly like to do my own thing Somewhat Social: sometimes I'm social, sometimes not Outgoing: like to socialize but enjoy time to myself Very social: I like to be connected with other people most of the time
"When you recommend products or services to friends, people usually?"	Not sure Go find out more about the product and determine if they need/want it Go out and buy the product
Product-related Characteristics	
"How often to you wear nail polish?" (category usage frequency)	5-point scale (1=Never, 5=All of the time)
"How familiar are you with the nail polish brand OPI?" (brand familiarity)	5-point scale (1=Not at all familiar, 5=Very familiar)
"What is your opinion of OPI nail polish?" (brand liking)	5-point scale (1=Very unfavorable, 5=Very favorable)
"How familiar are you with Nic's sticks from OPI?" (product familiarity)	5-point scale (1=Not at all familiar, 5= Very familiar)
"How likely are you to purchase Nic's Sticks from Nicole by OPI?" (product purchase likelihood)	10-point scale (1=Very unlikely, 5= Neither likely nor unlikely / not familiar with Nic's sticks, 10=Very likely)
"How likely are you to recommend Nic's Sticks from Nicole by OPI?" (product recommendation likelihood)	10-point scale (1=Very unlikely, 5= Neither likely nor unlikely / not familiar with Nic's sticks, 10=Very likely)

TABLE 2

MEASURES OF ONLINE AND OFFLINE SOCIAL INTERACTIONS

Type of Social Interaction (SI)		% of Members who Engaged in this SI
Online	Sent an email to a friend via SheSpeaks tell-a-friend tool	9.13
	Sent a personal email to others	25.09
	Wrote an entry in my blog	7.98
	SheSpeaks discussion board	28.10
	Another discussion board	13.48
	Posted comment on a shopping website (i.e., beauty.com)	5.94
	On a social networking site i.e. Facebook	8.78
Offline	In-person conversation	92.91
	Let them use my Nic’s Stick to see what they thought	49.83
	Over the phone	44.33
	Gave them Nic's Sticks coupons directly	49.38
	Left coupons where people would see them/pick them up	11.26

Note: in the survey, these types of social interactions were presented in a different order and were not classified as online versus offline.

TABLE 3
COUPON USAGE MODELS AND MODEL FIT

	Model 1	Model 2	Model 3	Model 4
Included covariates:				
Demographic	×	×	×	×
Product-related		×		×
Social			×	×
Model fit:				
Number of observations	1,032	1,032	1,032	1,032
Number of parameters	22	34	38	50
-2 log-likelihood	5,199.05	5,135.71	5,030.86	5,001.01
AIC	5,243.05	5,203.71	5,106.86	5,101.01

TABLE 4

PARAMETER ESTIMATES

Covariate	β_{self}		β_{other}	
	Estimate	***t*-value**	**Estimate**	***t*-value**
Age:				
Below 25 (baseline)	—	—	—	—
25 to 29	-.140	-.735	**.218*****	2.713
30 to 34	-.080	-.422	.133	1.681
35 to 39	**.461****	2.059	**.383*****	3.745
40 to 44	.224	.946	**.216****	2.152
45 to 49	.339	1.260	**.251****	2.170
50 and older	-.252	-.842	.147	1.206
Employment status (1 = employed full-time)	-.202	-1.569	**-.129****	-2.267
Category usage frequency	.085	1.094	**.097*****	2.932
Brand familiarity	-.033	-.603	**-.047****	-2.009
Brand liking	-.022	-.355	.018	.655
Product familiarity	**.242*****	2.775	**.108*****	2.661
Product purchase likelihood	-.051	-.783	**-.068****	-2.360
Product recommendation likelihood	.034	.538	.055	1.947
About how many people do you talk to on a daily basis?				
1-9 (baseline)	—	—	—	—
10-19	.275	1.658	**.192*****	2.926
20-29	**.433****	2.075	**.355*****	3.964
30+	.414	1.941	**.541*****	5.312
Which best describes you socially?				
Independent (baseline)	—	—	—	—
Somewhat Social	**1.626*****	3.848	.402	1.893
Outgoing	**1.589*****	3.819	**.442****	2.108
Very Social	**1.819*****	4.187	**.611*****	2.816
When you recommend products or services to friends, people usually?				
Not sure (baseline)	—	—	—	—
Go find out more about the product and determine if they need/want it	.140	.607	**.199****	2.157
Go out and buy the product	**.521****	2.131	**.380*****	3.798

** $p < .05$, *** $p < .01$.

TABLE 5

INTERCEPTS, DISCOUNTING, AND COST PARAMETERS

Parameter	**Estimate**	***t*-value**
Self-usage intercept	.803	.199
Other-usage intercept	-.069	-.244
Discount parameter on self-usage utility (γ_{self})	**.466*****	3.180
Discount parameter on other-usage utility (γ_{other})	**.957*****	17.939
Discount parameter on self-usage cost (λ_{self})	**.699*****	3.134
Discount parameter on other-usage cost (λ_{other})	.000[a]	—
Unit cost of self-usage (θ_{self})	2.343	.607
Unit cost of other-usage (θ_{other})	**1.734*****	7.192

** $p < .05$, *** $p < .01$.

[a] Parameter estimate was at lower-bound of constraint ($\lambda_{other} \geq 0$).

TABLE 6

IMPACT OF COVARIATES ON COUPON SHARING (BASED ON FULL MODEL)

Quartiles based on:	**All Covariates**	**Social Covariates**	**Product Covariates**
	Average Number of Coupons Shared with Others		
Quartile 1	2.40	2.32	2.53
Quartile 2	2.84	2.96	3.15
Quartile 3	3.32	3.19	3.28
Quartile 4	3.64	3.72	3.24

TABLE 7

IMPACT OF COVARIATES ON COUPON SHARING (BASED ON RESTRICTED MODELS)

Quartiles based on:	**Social Covariates (Model 3)**	**Product Covariates (Model 2)**
	Average Number of Coupons Shared with Others	
Quartile 1	2.40	2.55
Quartile 2	2.94	3.09
Quartile 3	3.19	3.24
Quartile 4	3.72	3.33

TABLE 8

IMPACT OF COVARIATES ON COUPON SHARING (BASED ON FULL MODEL) – CAMPAIGN 2

Quartiles based on:	**All Covariates**	**Social Covariates**	**Product Covariates**	**Social Covariates with Campaign 1 estimates**
		Average Number of Coupons Shared with Others		
Quartile 1	3.10	3.13	3.40	3.23
Quartile 2	3.54	3.52	3.49	3.40
Quartile 3	3.57	3.61	3.43	3.59
Quartile 4	3.76	3.76	3.65	3.75

APPENDIX

TABLE A1

MODEL 2: PARAMETER ESTIMATES

Covariate	β_{self}		β_{other}	
	Estimate	***t*-value**	**Estimate**	***t*-value**
Age:				
Below 25 (baseline)	—	—	—	—
25 to 29	-.102	-.577	**.248*****	2.730
30 to 34	-.018	-.100	**.193****	2.142
35 to 39	**.498****	2.409	**.482*****	4.067
40 to 44	.212	.978	**.248****	2.153
45 to 49	.375	1.519	**.302****	2.268
50 and older	-.205	-.740	.152	1.095
Employment status (1 = employed full-time)	-.078	-.702	.007	.122
Category usage frequency	**.151****	2.160	**.192*****	4.924
Brand familiarity	.010	.206	-.018	-.669
Brand liking	-.041	-.718	-.003	-.087
Product familiarity	**.254*****	3.148	**.153*****	3.266
Product purchase likelihood	-.044	-.724	**-.076****	-2.335
Product recommendation likelihood	.047	.801	**.079****	2.427
About how many people do you talk to on a daily basis?				
1-9 (baseline)	—	—	—	—
10-19	—	—	—	—
20-29	—	—	—	—
30+	—	—	—	—
Which best describes you socially?				
Independent (baseline)	—	—	—	—
Somewhat Social	—	—	—	—
Outgoing	—	—	—	—
Very Social	—	—	—	—
When you recommend products or services to friends, people usually?				
Not sure (baseline)	—	—	—	—
Go find out more about the product and determine if they need/want it	—	—	—	—
Go out and buy the product	—	—	—	—

** $p < .05$, *** $p < .01$.

TABLE A2

MODEL 2: INTERCEPTS, DISCOUNTING, AND COST PARAMETERS

Parameter	**Estimate**	***t*-value**
Self-usage intercept	**295.134*****	1632.150
Other-usage intercept	**1.016*****	3.965
Discount parameter on self-usage utility (γ_{self})	**.557*****	7.874
Discount parameter on other-usage utility (γ_{other})	**.864*****	15.599
Discount parameter on self-usage cost (λ_{self})	**.560*****	7.921
Discount parameter on other-usage cost (λ_{other})	.000[a]	—
Unit cost of self-usage (θ_{self})	**294.721*****	1629.868
Unit cost of other-usage (θ_{other})	**2.105*****	6.991

* $p < .10$, ** $p < .05$, *** $p < .01$.

[a] Parameter estimate was at lower-bound of constraint ($\lambda_{other} \geq 0$).

TABLE A3

MODEL 3: PARAMETER ESTIMATES

Covariate	β_{self}		β_{other}	
	Estimate	***t*-value**	**Estimate**	***t*-value**
Age:				
Below 25 (baseline)	—	—	—	—
25 to 29	-.230	-1.196	**.174****	2.188
30 to 34	-.175	-.914	.083	1.059
35 to 39	.377	1.677	**.339*****	3.363
40 to 44	.157	.660	.171	1.725
45 to 49	.286	1.060	.218	1.896
50 and older	-.323	-1.080	.126	1.035
Employment status (1 = employed full-time)	-.234	-1.802	**-.158*****	-2.728
Category usage frequency	—	—	—	—
Brand familiarity	—	—	—	—
Brand liking	—	—	—	—
Product familiarity	—	—	—	—
Product purchase likelihood	—	—	—	—
Product recommendation likelihood	—	—	—	—
About how many people do you talk to on a daily basis?				
1-9 (baseline)	—	—	—	—
10-19	**.332****	1.987	**.225*****	3.383
20-29	**.485****	2.311	**.390*****	4.280
30+	**.463****	2.155	**.573*****	5.526
Which best describes you socially?				
Independent (baseline)	—	—	—	—
Somewhat Social	**1.652*****	3.846	.398[a]	1.914
Outgoing	**1.634*****	3.861	**.458****	2.244
Very Social	**1.917*****	4.351	**.660*****	3.107
When you recommend products or services to friends, people usually?				
Not sure (baseline)	—	—	—	—
Go find out more about the product and determine if they need/want it	.149	.634	**.200****	2.144
Go out and buy the product	**.556****	2.245	**.395*****	3.903

** $p < .05$, *** $p < .01$.

[a]: $p = .056$.

TABLE A4

MODEL 3: INTERCEPTS, DISCOUNTING, AND COST PARAMETERS

Parameter	**Estimate**	***t*-value**
Self-usage intercept	-.018	-.008
Other-usage intercept	-.245	-1.047
Discount parameter on self-usage utility (γ_{self})	**.429*****	2.921
Discount parameter on other-usage utility (γ_{other})	**.944*****	17.741
Discount parameter on self-usage cost (λ_{self})	**.743*****	3.318
Discount parameter on other-usage cost (λ_{other})	.000[a]	—
Unit cost of self-usage (θ_{self})	1.673	.787
Unit cost of other-usage (θ_{other})	**1.810*****	7.285

** $p < .05$, *** $p < .01$.

[a] Parameter estimate was at lower-bound of constraint ($\lambda_{other} \geq 0$).