How to Better Target and Incent Paid Endorsers in Social Advertising Campaigns: A Field Experiment

Completed Research Paper

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Abstract

We investigate paid endorsement as a crowd-sourcing social advertising mechanism that allows advertisers to bypass publishers (e.g., Facebook) and recruit individual endorsers of their own choice at affordable prices. Specifically, we investigate (i) how incentives affect endorsers' participation and effectiveness, (ii) what types of endorsers are most effective in generating online engagement (likes, comments, and retweets), and (iii) the potential differences between generating different types of engagements. We conduct a large scale field experiment in which we manipulate exogenously pay rates and eligibility to participate. Our findings suggest that increasing financial incentive doesn't necessarily improve participation rate. In addition, endorsers who are effective are often not responsive. Further, it can be misleading to assess the attractiveness of endorsers simply based on observed engagements. Our findings provide new insights on how marketers can improve the effectiveness of paid endorsement by identifying and incentivizing high potential endorsers.

Keywords: Paid Endorsement, Social Advertising, Targeting, Incentives, Engagement

Introduction

Social advertising leverages social connections among consumers to reach and influence a target audience. This business practice is becoming increasingly popular. According to BI intelligence[1], social advertising spending in the US will top $8.5 billion in 2015 and reach nearly $14 billion by 2018. Globally, it will reach $23.7 billion in 2015 and $36 billion by 2017, capturing 16% share of all digital ad spending[2]. Two thirds of marketers believe that social media is core to their business, and 70% of them plan to increase the budget on social media marketing[3].

The prevalent social advertising mechanism is a centralized system in which advertisers submit ads to social media platforms (publishers) and those platforms then decide how to distribute the ads. Two drawbacks of this centralized mechanism are that advertisers have no direct control over the selection of endorsers (e.g., users who share/retweet an ad on Facebook/Twitter) and that endorsers are not incentivized to get engaged. Paid endorsement, in contrast, is a decentralized social advertising mechanism that allows advertisers to bypass publishers and recruit individual endorsers of their own choice at pre-specified prices. Specifically, advertisers post tasks asking users to post or retweet some ad on a paid endorsement platform

[1] http://www.businessinsider.com/social-media-advertising-spending-growth-2014-9
[2] http://www.emarketer.com/Article/Social-Network-Ad-Spending-Hit-2368-Billion-Worldwide-2015/1012357
[3] http://www.adweek.com/socialtimes/social-marketing-2015/504357

(a broker website similar to Amazon Mechanical Turk) and microbloggers registered on the platform can take on the tasks for monetary rewards. Paid endorsement has gained particular popularity in China, with more than 10 websites acting as platforms for paid endorsement. Weibo.com, the largest Chinese microblog site with more than 500 million users, also launched its official paid endorsement platform in 2012.

Despite the growing interest in paid endorsement and social advertising in general, its effectiveness remains in question. Two thirds of advertisers are uncertain about the effectiveness of social advertising[4&5]. The effectiveness of a paid endorsement campaign depends on how many endorsers participate and on how well the participants expand reach (i.e., views), generate engagement (i.e., likes, comments, and retweets), increase traffic (i.e., clicks), and boost sales.

This paper focuses on the effectiveness of paid endorsers in generating engagement. Customer engagement is a key objective to marketers and can easily be tracked at the endorser/user level. A number of studies have investigated how characteristics of online users is associated with their influence on others (Aral and Walker 2012; Katona et al. 2011; Trusov et al. 2010). However, these studies concentrate on organic word of mouth and voluntary endorsement without financial incentive (Shi et al. 2014). Their findings need not generalize to paid endorsement campaigns with financial incentives. For instance, self-presentation is often a key motive to post online content (Schau and Gilly 2003; Toubia and Stephen 2013), but it is not clear to what extent this holds for paid endorsement and other viral-for-hire campaigns.

In an attempt to fill the above gap in the literature, this paper aims at understanding how to effectively target and incent paid endorsers in social advertising campaigns, so as to improve the overall effectiveness of such campaigns. In particular, we are interested in the following questions: (i) how incentives affect endorsers' participation and effectiveness in paid endorsement campaigns, (ii) what types of endorsers are most effective in generating online engagements (likes, comments, and retweets), and (iii) the potential differences between engagements that require different levels of efforts from fans.

To answer the above questions, we collaborate with two vendors on taobao.com and run a field experiment to spread product information on weibo.com, using one of the largest Chinese paid endorsement platforms (i.e., weituitui.com). For identification purpose, we exogenously manipulate the pay rate to endorsers and their eligibility to participate. Since the data collected from our experiment are panel counting data with sample selection issues, we propose a Poisson lognormal model with sample selection and correlated random effects to analyze what affects endorsers' participation and effectiveness. Our study produces several intriguing findings: 1) increasing the pay rate doesn't improve participation rate; 2) the characteristics of endorsers often have opposite effects on participation and effectiveness; 3) low potential endorsers may generate high observable engagements due to their high probability to participate, whereas high potential endorsers may generate low observable engagements due to their low probability to participate; 4) the potential of the same endorser can be different in generating different types of engagement.

Our work makes the following contributions to the literature. First, it represents the first attempt to study what affects endorsers' participation and effectiveness in paid endorsement campaigns. Second, this paper highlights the difference between potential effectiveness and observable effectiveness. Third, it sheds light on the mechanisms driving different types of engagements. Finally, this paper makes a methodological contribution, providing a general framework to deal with the sample selection problem in panel data with repeated observations.

Theoretical Foundations

Participation

The literature on survey studies have broadly divide the reasons regarding why people participate in surveys into three categories: altruistic reasons (e.g., willingness to help research and civil duty), egoistic reasons (e.g., monetary incentive, opportunity to learn something), and survey-specific reasons (e.g., topical interest, trust in organization) (Singer and Ye 2013). Likewise, in paid endorsement campaigns, the

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[4] http://www.nielsen.com/content/dam/corporate/us/en/reports-downloads/2013%20Reports/Nielsen-Paid-Social-Media-Adv-Report-2013.pdf

[5] http://www.socialmediaexaminer.com/SocialMediaMarketingIndustryReport2014.pdf

motivators of endorsers can be loosely classified into three categories: altruistic (e.g., goodwill to share attractive deals), egoistic (e.g., monetary incentive and self-enhancement), and campaign-specific. Since this study is not interested in campaign- or product-specific attributes, two particularly relevant drivers of participation are monetary incentive and self-enhancement.

Monetary Incentive. There is a large body of research on the effect of incentive size on response rates of surveys. The common finding is that incentive increases responses rates, across different modes of surveys including mail surveys (Church 1993; Edwards et al. 2002), interview-mediated surveys (Cantor et al. 2008), and Internet surveys (Göritz 2006). However, there is no consensus on how big the incentive should be. In addition, whether incentive has an effect may depends on whether the incentive is prepaid or promised (i.e., payment is contingent on the completion of task). Church (1993) shows that incentives only have a consistent and significant positive effect on response rates if they are prepaid instead of promised. Cantor et al. (2008) find that prepaid incentive between $1-5 increases response rates, but promised incentive between $5-25 does not increase response rates as compared to no incentive condition, though even larger promised incentive may have effects. In a paid endorsement campaign, incentive is promised rather than prepaid, as endorsers won't be paid until their responses are approved. Therefore, the effect of incentive in paid endorsement might be dampened when it's promised rather than prepaid.

Self-enhancement. In online communities, users are intrinsically motivated to establish high self-image or social status (Schau and Gilly 2003; Toubia and Stephen 2013). In particular, Toubia and Stephen (2013) documented that self-image is the primary motive for most users to contribute content voluntarily to Twitter. Since the activities of users on social media platforms are often visible to all their friends/fans, they might be reluctant to share content that makes them look bad (Barasch and Berger 2014). Therefore, users with a positive reputation and self-image may be more selective than others in which paid endorsement campaigns to participate.

The concern about self-enhancement varies with the characteristics of endorsers. In this paper, we focus on three categories of characteristics of endorsers, namely social media fan base, prior activity level, and community embeddedness.

Social media fan base refers to the number of fans that endorsers on social media platforms have. Since the remuneration of endorsers often increases with their number of fans, endorsers with a larger number of fans might be financially more motivated to participate. However, users with a larger number of fans may derive more self-image related utilities (Toubia and Stephen 2013). As a result, they might be more selective in which campaigns to participate, as broadcasting irrelevant content can hurt their reputation (Barasch and Berger 2014; Bock et al. 2005). Alternatively, it's possible that endorsers with a greater number of fans are more likely to participate regardless of financial incentive, as they derive more intrinsic and status-related benefits from relaying attractive deals (Toubia and Stephen 2013).

Prior activity level refers to the endorsers' past activity intensity on social media and paid endorsement platforms. The more posts a user made on social media, and the more campaigns a user participated in, the less selective the user is in deciding what to post and what to participate in, the more likely they are spammers who derive high utility from monetary incentive but low utility from non-monetary incentive (Porter and Whitcomb 2003). Therefore, we expect endorsers who posted more and participated more in the past to be more likely to participate in a future campaign.

Community embeddedness refers to how long the endorsers have been registered and how many friends the endorser have in the paid endorsement community. Endorsers who are more deeply embedded into the community might be more selective in what to participate in (Minkler 2012), and more concerned about their status when sharing content in online communities (Schau and Gilly 2003; Toubia and Stephen 2013). Thus, endorsers who have registered longer and have more friends in the paid endorsement community might be more selective and less responsive to paid endorsement campaigns.

Effectiveness

The effectiveness of endorsers in generating engagements depends on the level of effort, the trust of their fans on the endorsers, the sheer numbers of fans, and the tie strength with individual fans (Chu and Kim 2011; King et al. 2014). We discuss the potential effects of incentive size and endorsers' characteristics based on how they impact these constructs.

In paid endorsement platforms, the remuneration of endorsers are often determined solely based on their number of fans rather than contingent on performance. When incentive does not depend on performance, there are two alternative hypotheses in the survey literature regarding the impact of incentive on response quality (Cantor et al. 2008; Singer and Ye 2013). One hypothesis is that, by inducing samples who would otherwise not participate, the quality of responses will decline. The alternative hypothesis is that, by rewarding participants, the quality of responses will increase due to feel of gratitude or obligation. Interestingly, a comprehensive review of studies evaluating the effects of incentive on response quality (e.g., number of questions answered and length of answers) concluded that incentive size almost never had an effect on quality (Singer and Ye 2013). This suggests that in paid endorsement campaigns, the size of incentive is not likely to impact the effort of endorsers. Therefore, we expect little to no effect of incentive on effectiveness.

Characteristics associated with self-enhancement may affect not only participation, as discussed above, but also effectiveness, be it in possibly opposite directions.

Social media fan base. While the tie strength between users and their contacts decrease with their number of contacts (Burke 2011; Roberts et al. 2009; Katona et al. 2011) a larger fan base implies a larger number of audience who can potentially engage. A number of studies have investigated the effect of network size on a user's overall influence, but the results are mixed. Katona et al. (2011) find that the effectiveness of individuals in influencing friends to adopt (register) a social network site decreases with the total number of their contacts, whereas Yoganarasimhan (2012) finds that a node's overall effectiveness in spreading Youtube videos increases with its network size. One explanation to reconcile these two findings is that the effect of network size depends on the level of effort needed to make a decision. When the required effort is small (e.g., information diffusion, liking a post), weak tie strength (Granovetter 1973; Weimann 1983) suffices and the effect of network size is dominated by volume per se, leading to a positive overall effect. On the other hand, when the required effort is large (e.g., adoption, commenting or retweeting a posts), the need for strong tie strength (Weenig and Midden 1991; Weimann 1983) make users with larger number of fans connected by weak ties not as persuasive, resulting in a negative overall effect. In this sense, the effect of fans on comments and retweets might be smaller than that on likes, as comments and retweets requires more effort than likes.

Priority activity level. As we mentioned earlier, endorsers who posted and participated a lot in the past are more likely to be spammers. Numerous posts or endorsements can hurt their reputation, rendering them less trustworthy than those who don't post/endorse as much (Barasch and Berger 2014; Bock et al. 2005). Therefore, endorsers who posted and participated more in the past should be less effective. Endorser characteristics associated with prior activity may have opposite effects on participation and effectiveness.

Community embeddedness. Following the argument that endorsers who are more embedded to the paid endorsement community tend to be more selective in what to participate, it's likely that their follower will trust them more. Consequently, more embedded endorsers are expected to be more effective in generating online engagements from their fans. Endorser characteristics associated with community embeddedness may have opposite effects in participation and effectiveness.

Field Experiment

Design

We designed and ran a field experiment on weituitui.com, which has more than 100K registered endorsers active on microblogs (primarily weibo.com). Weituitui.com is a broker website that allows advertisers to recruit endorsers at pre-specified prices for their social media marketing campaigns. Figure 1 shows the workflow of a paid endorsement campaign on weituitui.com.

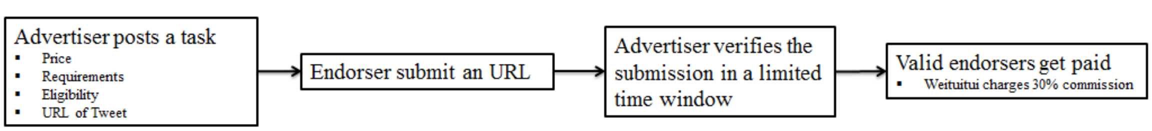

Figure 1. Workflow of Paid Endorsement on Weituitui.com

To initiate a paid endorsement campaign, an advertiser first posts a task describing her needs onto weituitui.com. In the task, the advertiser can specify how much an endorser will be paid. While the amount of reward for an endorser is solely determined by her number of fans, the advertiser can choose between a linear pricing scheme (i.e., amount of reward is price or pay rate per fan times the number of fans) and a more flexible tiered pricing scheme (i.e., amount of reward is a step-wise linear function of fans, given by the advertiser). In order to rule out the effects of robots and inactive fans, weituitui.com uses the number of verified fans, instead of the number of nominal fans on microblog, to calculate the reward for an endorser. The number of verified fans is the number of nominal fans times a coefficient representing the quality of fans (i.e., verified ratio). Weituitui.com has an internal algorithm to compute this coefficient based on how actively an endorser's fans engage on her past statuses (tweets/retweets).

In a task, the advertiser provides the URL of the target tweet containing the product information. The advertiser can impose some written requirements for the task, such as how long the endorser should keep (i.e., not delete) the retweet on their timeline, and the minimal length of the comment in the retweet. Furthermore, the advertiser can specify who is eligible for the task. Some eligibility restrictions are hard restrictions automatized by the platform, such as the allowable day part of participation (e.g., 9am-9pm), while other are soft restrictions attached in the written requirements that needs to be manually verified afterwards. If an endorser decides to participate, she needs to retweet the given tweet, fulfill the requirements, and then submit the URL of her retweet. The duration of a task ranges from 3 to 5 days. Once the task ends, the advertiser has 3 days to manually approve or disapprove the submissions, depending on whether the endorser has truly retweeted the given tweet and fulfilled the requirements. All remaining submissions are approved automatically by the platform after the 3-day window. Because of this auto-approval policy, opportunistic endorsers or spammers may submit a random URL even if they haven't retweeted the tweet. For approved tasks, the endorsers will be paid, and weituitui charges 30% as a commission fee.

To investigate the effect of financial incentive on endorsers' willingness to participate and effectiveness in generating engagements (i.e., likes, comments, and retweets), we exogenously manipulate financial incentive by posting two identical tasks at two different levels of prices or pay rates. We use the linear pricing scheme as it's easier to implement and understand. The two price levels are chosen as 0.0002 RMB (1RMB ≈ 0.16USD) and 0.0004 RMB per fan, respectively. The former is the lowest possible and most common rate for linear pricing (i.e., 87% of tasks), whereas the latter is higher than or equal to 96% of linear rates used on weituitui.com. To make sure that the two tasks are indeed identical and yet independent with each other, we register a new account on weibo.com and post two identical tweets on the same product at roughly the same time (more precisely, one is posted just seconds ahead of the other). The URLs of the two tweets are then used in the two tasks, respectively. Since the new account has no fans, all the observed engagements on the two tweets come from the paid endorsers and their fans. To eliminate the potential effects resulting from the order of the two tweets, the price levels associated with the firstly and secondly posted tweets are swapped from time to time.

In order to identify the effects of endorsers' characteristics on participation and effectiveness, we need an exclusive variable that affects participation but not effectiveness, or the other way around. The underlying reason is that there might be unobserved variables that affect both participation and effectiveness, causing the well-known sample selection problem (Heckman 1979). While this problem can be addressed by well-designed sample selection models, the identification of such models typically requires an exclusive variable in practice (Puhani 2000). Toward that end, we add a soft eligibility restriction in our tasks, such that every user on weituitui.com is only eligible for one of the two identical tasks. The word "soft" means ineligible users can still participate, but just won't be paid. To make sure that the soft eligibility restriction is exogenous, we use the last two digits of an endorser's ID (a six-digit number) on weituitui.com to determine her eligibility for the two tasks. The last two digits of an endorser's ID are assigned randomly, as confirmed by the manager of weituitui.com. As a check, we found the last two digits to indeed be uncorrelated with any observed covariate in our data. The above design allows us to identify the effects of both financial incentive and endorsers' characteristics in participation and effectiveness.

Our experiment was conducted in 8 different weeks between 2/1/2014 and 4/26/2014. Each week, we posted two groups (pairs) of identical tasks on two products from the same vendor. Accordingly, we divided endorsers into 4 different groups based on their ID (i.e., 00~24, 25~49, 50~74, 75~99), such that any endorser was eligible for only one of the four tasks in that week. The tasks were rotated over 6 products from 2 vendors on taobao.com. For our experiment, we did not impose any particular task requirements except for retweeting and liking the tweet. The eligible price levels for the same endorsers were rotated across weeks. Table 1 visualizes the key conditions of our experimental design by showing the four tasks posted in a given week. Each task pertains to one of two products for which endorsers are promised either a high or low pay rate, and a potential endorser qualifies for only one of the four tasks.

Table 1. Experiment Design in a Given Week (Eligible IDs shown in cells)*

	Product A	Product B
Price: 0.0002 RMB/follower	00~24	50~74
Price: 0.0004 RMB/follower	25~49	75~99

* Eligible IDs were rotated across price levels and products across weeks.

Data

For the purpose of this study, the data is processed at the endorser level. We focus on the 8,283 active endorsers who have participated in at least one paid endorsement task in the past 6 months. In every task, we record whether an endorser participates and how many engagements she generates, if participating. The numbers of engagements are collected for each retweet (each endorser in other words) using the API provided by weibo.com. Herein, "participates" means that an endorser has actually retweeted the message, as only true retweeters can generate engagements. The participation and engagement statistics are summarized in Table 2. Excluding one task in week 6 for which we fail to track the engagements of participated endorsers due to a technical issue, the remaining 31 tasks have attracted 2,241 participations (i.e., paid retweets) from 1,016 endorsers.

Table 2. Experiment Statistics

Number of weeks	8
Number of tasks	31
Number of vendors	3
Number of products	6
Number of endorsers	8,283
Number of participated endorsers	1,016
Number of participations	2,241
Number of participations from ineligible endorsers	91
Number of observations	236,008
Average Number of participations per task	72.3
Average Number of likes per participation	0.10
Average Number of comments per participation	0.22
Average Number of retweets per participation	0.23

The distribution of engagements generated by individual endorsers are shown in Table 3. The great majority of retweets from paid endorsers doesn't generate any further engagements.

Table 3. Distribution of Engagements Generated by Individual Endorsers

Type \ **# Engagements**	0	1	2	3	4	5~10	>10
likes	2072	145	14	4	4	1	1
comments	2104	69	21	15	5	16	11
retweets	2130	50	9	15	7	15	15

The dependent variables in our analysis are participation and effectiveness. Two of the independent variables, the price level and the eligibility, are manipulated. We also collect data on the characteristics of endorsers by scraping their profile information on weituitui.com and weibo.com. The profile information on weituitui.com include the number of verified fans, the number of tasks participated, the total amount of money earned, the total referral income, the number of friends on weituitui.com, and the registration duration of endorsers on weituitui.com. The profile information on weibo.com include the number of fans and the number of tweets (including retweets).

Table 4 organizes the independent variables into six different categories. Since our primary interest is with variables that advertisers can either manipulate or observe for targeting decisions in paid endorsement and other social media marketing campaigns, we focus on variables in four of the six categories: financial incentive, social media fan base, prior activity level, and community embeddedness.

Table 4. Description of Independent Variables

Variables	Description
Exclusive Variable	
isEligible	Whether a user is eligible for a given task (for selection equation only)
Financial Incentive	
price	Pay rate per fan (binary, either 0.0002 RMB/fan or 0.0004 RMB/fan)
Social Media Fan base	
fans	Number of fans on weibo.com
verifiedRatio	Percentage of verified fans in total fans
Prior Activity Level	
tweetNum	Number of tweets posted on weibo.com
taskNum	Total number of tasks participated in the past
qualifiedRatio	Percentage of qualified tasks in the past
Community Embeddedness	
regDuration	Number of days an endorser has registered on weituitui.com (rescaled to [0,1])
friends	Number of friends an endorser has on weituitui.com's internal social network
Others	
group	A dummy indicating which of the 16 groups a task belongs to
referralReward	Total reward received through referring others to register on weituitui.com
times	Number of times an endorser has participated in tasks on the same product

The summary statistics of the independent variables are shown in Table 5. The characteristics of participating endorsers are clearly different from those of the whole population, which is evidence of the earlier mentioned self-selection.

Table 5. Key Statistics on Independent Variables

Variables	All Endorsers					Participated Endorsers				
	Mean	Median	Min	Max	SD	Mean	Median	Min	Max	SD
isEligible	0.25	0.00	0.00	1.00	0.43	0.96	1.00	0.00	1.00	0.20
log(fans)	6.93	6.84	2.48	15.42	2.02	7.88	7.76	2.83	14.51	1.97
verifiedRatio	0.44	0.46	0.00	1.00	0.24	0.45	0.46	0.00	1.00	0.25
log(tweetNum)	5.90	5.99	0.00	11.26	1.75	6.57	6.66	0.00	11.26	1.61
log(taskNum)	2.48	2.30	0.00	8.70	1.87	4.54	4.76	0.00	8.70	1.81
qualifiedRatio	0.74	0.82	0.00	1.00	0.28	0.83	0.87	0.00	1.00	0.16
regDuration	0.21	0.18	0.00	1.00	0.15	0.21	0.17	0.00	1.00	0.19
log(friends)	0.38	0.00	0.00	2.77	0.71	0.60	0.00	0.00	2.77	0.90
log(referralReward)	-5.54	-6.91	-6.91	7.17	2.94	-4.69	-6.91	-6.91	5.45	3.55
times	0.02	0.00	0.00	4.00	0.15	0.09	0.00	0.00	4.00	0.32

Model

There are two technical challenges with analyzing our data. First, engagements are only observed for those endorsers who participated in our tasks, but their effectiveness may not be representative of the whole population. This is commonly known as the sample selection problem (Heckman 1979). Second, an endorser can participate in more than one task and the resulting observations on the same endorser may not be independent. While both the sample selection and repeated observation problems are common in the literature and can be addressed effectively when they appear separately, little has been done to address both problems jointly, especially when the dependent variable is counts. In this paper, we propose a novel methodology to deal with both problems. Throughout this paper, we use boldface letters to represent vectors and matrices. For notational compactness, we use row vectors throughout the paper.

Participation and Potential Effectiveness

There are two equations in our model: the first equation models what affects an endorser's willingness to participate (hereafter selection or participation equation), and the second equation models what affects an endorser's effectiveness in generating likes, comments, and retweets (hereafter outcome equation). Following the standard sample selection model (Greene 2009; Heckman 1979), we use a Probit model for the selection equation. Let the indicate variable z_{it} represent whether endorser i participates in task t, the participation decision is given by

$$z_{it} = \mathbf{1}(\boldsymbol{\alpha} \boldsymbol{w}'_{it} + \delta u_i + \xi_{it} > 0) \tag{1}$$

where the vector $\boldsymbol{w}_{it}$ includes an intercept and the set of variables that affects the participation decision of endorser i in task j. The variables in $\boldsymbol{w}_{it}$ include characteristics of endorser i, characteristics of task t, and the characteristics specific to the endorser-task dyad, including the exclusive variable isEligible (see Table 4). They also include 15 dummy variables for each pair of identical tasks posted that vary only on price or pay rate (the intercept captures the sixteenth pair). These dummies absorb any task-specific effect apart from price, like characteristics of the product featured, characteristics of our post on weituitui, and temporal shocks. The term $u_i \sim N(0,1)$ captures endorser level unobserved characteristics affecting the participation decision. $\xi_{it} \sim N(0,1)$ represents other unobserved dyadic factors that affect the participation decision. The selection equation given above is essentially a Probit model with random effects (Butler and Moffitt 1982).

Since the engagements including likes, comments, and retweets are all counts, we use a conditional Poisson model for the outcome equation. Let y^*_{it} be the potential outcome (i.e., likes, comments, or retweets) of endorser i on task t, the outcome equation is given by

$$E[y^*_{it} | \boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it}] = \lambda_{it} = \exp(\boldsymbol{\beta} \boldsymbol{x}'_{it} + \sigma \varepsilon_i + \gamma \epsilon_{it}) \tag{2}$$

where $\boldsymbol{x}_{it}$ includes an intercept and the set of variables that affects the potential engagements endorser i generated for task t. These variables are the same as those in $\boldsymbol{w}_{it}$, except for the exclusion restriction on isEligible. Our outcome equation accounts for two levels of heterogeneity. $\varepsilon_i \sim N(0,1)$ captures the effect of endorser level unobserved characteristics. $\epsilon_{it} \sim N(0,1)$ further captures the effect of dyadic endorser-task level unobserved characteristics. When $\sigma = 0$, Equation (2) simplifies to the Poisson lognormal model (Greene 2009), which often yields similar estimates with Negative Binomial Model. We find the above model is substantially superior to zero-inflated models such as zero-inflated Poisson in accounting for the excessive zeros in the data (see Table 3). Note that the error terms for different types of engagement might be correlated. However, since the three types of engagements have exactly the same set of regressors, estimating the equations for different types of engagements independently, as if there are no correlation across engagements, will give identical estimates (Kruskal 1968).

The error terms in the selection equation and the outcome equation are often not independent. Specifically, the endorser level unobserved characteristics that affect the selection equation may also affect the outcome equation, and so are the endorser-task level unobserved characteristics. As a result, we further assume that the endorser level and endorser-task level error terms are bivariate normally distributed, with a correlation of ρ and τ, respectively.

$$\begin{pmatrix} u_i \\ \varepsilon_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right), \begin{pmatrix} \xi_{it} \\ \epsilon_{it} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \tau \\ \tau & 1 \end{pmatrix}\right).$$

As compared to the existing sample selection models (Greene 2009; Heckman 1979; Winkelmann 1998), our model not only takes into account random effects, but also further allows the random effects to be correlated. This substantially increases the complexity of our model. Let T_i be the number of tasks endorser i can potentially participate, the likelihood of all observations on endorser i can be written as

$$L_i = P\left(y^*_{i1}, \dots, y^*_{iT_i}; z_{i1}, \dots, z_{iT_i} \middle| \boldsymbol{x}_{i1}, \dots, \boldsymbol{x}_{iT_i}, \boldsymbol{w}_{i1}, \dots, \boldsymbol{w}_{iT_i}\right)$$

$$= \int_{-\infty}^{\infty} \phi(\varepsilon_i) d\varepsilon_i \int_{-\infty}^{\infty} f(u_i|\varepsilon_i) du_i \prod_{t=1}^{T_i} \int_{-\infty}^{\infty} P(y_{it}^*|\boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it})^{z_{it}} P(z_{it}|\boldsymbol{w}_{it}, u_i, \epsilon_{it}) \phi(\epsilon_{it}) d\epsilon_{it} \quad (3)$$

where $P(y_{it}^*|\boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it}) = \frac{\lambda_{it}{}^{y_{it}} e^{-\lambda_{it}}}{y_{it}!}$, as given by the conditional Poisson distribution. In the likelihood function, $P(y_{it}^*|\boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it})$ only factors in when $z_{it} = 1$, as y_{it}^* is only observed for participated endorsers. The conditional density $f(u_i|\varepsilon_i)$ can be easily derived based on the bivariate normal distribution. The above likelihood does not have a closed-form representation. However, it can be numerically approximated by Gauss-Hermite Quadrature method (the mathematical details are available upon request). Therefore, the parameters in our model can be estimated by maximizing the approximated likelihood. Note that by changing the distributional assumption on $P(y_{it}^*|\boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it})$, our model can be easily adapted to deal with outcomes following other distributions.

Observable Effectiveness

One important question of interest to marketers is how much the mean potential outcome $E[y_{it}^*|\boldsymbol{x}_{it}]$ changes with respect to the changes in $\boldsymbol{x}_{it}$, namely $\partial E[y_{it}^*|\boldsymbol{x}_{it}]/\partial \boldsymbol{x}_{it}$. Integrating out ε_i and ϵ_{it} in equation (2) yields

$$E[\boldsymbol{y}_{it}^*|\boldsymbol{x}_{it}] = E_{\varepsilon_i} E_{\epsilon_{it}}\left[E[\boldsymbol{y}_{it}^*|\boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it}]\right] = \exp\left(\boldsymbol{\beta}\boldsymbol{x}_{it}' + \frac{\sigma^2+\gamma^2}{2}\right) \quad (4)$$

From equation (4), the relative partial effects of $\boldsymbol{x}_{it}$ on $E[y_{it}^*|\boldsymbol{x}_{it}]$ can be computed as

$$\boldsymbol{h}_{x_{it}} = \frac{1}{E\left[\boldsymbol{y}_{it}^*|\boldsymbol{x}_{it}\right]} \frac{\partial E\left[\boldsymbol{y}_{it}^*|\boldsymbol{x}_{it}\right]}{\partial x_{it}} = \frac{\partial \log E\left[\boldsymbol{y}_{it}^*|\boldsymbol{x}_{it}\right]}{\partial x_{it}} = \boldsymbol{\beta} \quad (5)$$

The relative partial effects of $\boldsymbol{x}_{it}$ on the conditional mean potential outcome $E[y_{it}^*|\boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it}]$ coincide with its partial effects on the unconditional (i.e., not conditional on any unobserved variable) mean potential outcome $E[y_{it}^*|\boldsymbol{x}_{it}]$. The absolute partial effects of $\boldsymbol{x}_{it}$ on $E[y_{it}^*|\boldsymbol{x}_{it}]$ is $\exp\left(\beta \boldsymbol{x}_{it}' + \frac{\sigma^2+\gamma^2}{2}\right)\beta$. In this paper, we focus on the relative partial effects as they are robust and scale-free. The absolute partial effects are highly sensitive to outliers in the data due to the exponential term $\exp\left(\beta \boldsymbol{x}_{it}' + \frac{\sigma^2+\gamma^2}{2}\right)$.

In addition to how individual variables impact the potential outcome, in practice, advertisers are often also interested in how these variables impact the actual or observable outcome. If an endorser chooses not to participate, the observable engagements generated would be zero. Therefore, the relationship between the observable outcome y_{it} and the potential outcome y_{it}^* can be written as

$$y_{it} = z_{it} y_{it}^* \quad (6)$$

Given that z_{it} and y_{it}^* are independent, conditional on $\boldsymbol{x}_{it}, \boldsymbol{w}_{it}, u_i, \varepsilon_i, \epsilon_{it}$, the conditional mean observable outcome can be written as

$$E[y_{it}|\boldsymbol{x}_{it}, \boldsymbol{w}_{it}, u_i, \varepsilon_i, \epsilon_{it}] = P(z_{it} = 1|\boldsymbol{w}_{it}, u_i, \epsilon_{it}) E[y_{it}^*|\boldsymbol{x}_{it}, \varepsilon_i, \epsilon_{it}] \quad (7)$$

The unconditional (i.e., not conditional on any unobserved variable) mean observable outcome can be obtained by integrating out u_i, ε_i and ϵ_{it} in equation (7).

$$E[y_{it}|\boldsymbol{x}_{it}, \boldsymbol{w}_{it}] = E_{u_i} E_{\varepsilon_i|u_i} E_{\epsilon_{it}}\left[E[y_{it}|\boldsymbol{x}_{it}, \boldsymbol{w}_{it}, u_i, \varepsilon_i, \epsilon_{it}]\right]$$

$$= \frac{1}{2\pi} exp\left(\boldsymbol{\beta}\boldsymbol{x}_{it}' + \frac{\sigma^2+\gamma^2}{2}\right) \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} \Phi\left(\frac{\boldsymbol{\alpha}' \boldsymbol{w}_{it} + \delta u_i + \tau \epsilon_{it}}{\sqrt{1-\tau^2}}\right) e^{-\frac{(\epsilon_{it}-\gamma)^2}{2}} d\epsilon_{it}\right] e^{-\frac{(u_i-\rho\sigma)^2}{2}} du_i \quad (8)$$

The relative partial effect of a variable s_{it} on the mean observable outcome can be written as

$$g_{s_{it}} = \frac{\partial \log E[\boldsymbol{y}_{it}|\boldsymbol{x}_{it}, \boldsymbol{w}_{it}]}{\partial s_{it}} = c\alpha_s + \beta_s \quad (9)$$

where α_s represents the corresponding coefficient in $\boldsymbol{\alpha}$ if s_{it} belongs to $\boldsymbol{w}_{it}$, otherwise 0. Similarly, β_s represents the corresponding coefficient in $\boldsymbol{\beta}$ if s_{it} belongs to $\boldsymbol{x}_{it}$, otherwise 0. The functional form of coefficient c, which is guaranteed to be positive, is given below.

$$c = \frac{\int_{-\infty}^{\infty}\left[\int_{-\infty}^{\infty}\phi\left(\frac{\alpha w'_{it}+\sqrt{2}\delta r+\rho\sigma\delta+\tau\gamma+\sqrt{2}\tau v}{\sqrt{1-\tau^2}}\right)e^{-v^2}dv\right]e^{-r^2}dr}{\sqrt{1-\tau^2}\int_{-\infty}^{\infty}\left[\int_{-\infty}^{\infty}\Phi\left(\frac{\alpha w'_{it}+\sqrt{2}\delta r+\rho\sigma\delta+\tau\gamma+\sqrt{2}\tau v}{\sqrt{1-\tau^2}}\right)e^{-v^2}dv\right]e^{-r^2}dr} > 0 \tag{10}$$

The standard errors of the relative partial effects can be estimated by the delta method.

Results

Participation and Potential Effectiveness

The parameter estimates of our model are shown in Table 6. For easier comparison, the parameters for each type of engagements are displayed in two columns side by side: one for the participation equation and the other for the outcome equation. All the structural parameters, including heterogeneity and correlation, are shown in the outcome column. We discuss our findings in order.

Table 6. Parameter Estimates for Different Types of Engagements

	Participation			Outcome		
	likes	**comments**	**retweets**	**likes**	**comments**	**retweets**
Exclusive Variable						
isEligible	2.559***	2.536***	2.54***			
Financial Incentive						
price=0.0002	-0.019	-0.019	-0.019	0.127	0.172	0.163
Social Media Fan base						
log(fans)	0.135***	0.125***	0.123***	0.184**	-0.075	-0.044
verifiedRatio	0.6***	0.612***	0.565***	0.441	1.151*	0.563
Prior Activity Level						
log(tweetNum)	0.044*	0.056**	0.053**	0.038	-0.336***	-0.398***
log(taskNum)	0.54***	0.551***	0.546***	-0.325***	-0.467***	-0.644***
qualifiedRatio	-0.021	-0.022	-0.02	0.648	1.253.	-0.476
Community Embeddedness						
regDuration	-4.398***	-4.382***	-4.269***	-0.11	2.211*	3.574***
log(friends)	-0.099**	-0.112**	-0.095*	0.427**	0.246	0.533*
Others						
log(referralReward))	-0.018*	-0.02*	-0.022*	0.01	-0.062	-0.034
times	-0.144**	-0.15***	-0.162***	-0.252	-0.466	0.043
Heterogeneity						
δ				1.366***	1.358***	1.352***
σ				1.549***	1.953***	2.797***
γ				0.204	1.542***	1.484***
Correlation						
ρ				-0.187***	-0.307***	-0.268***
τ				0.005	0.132	0.293*
Log Likelihood				-7270.49	-7349.59	-7261.07

* Significance codes: "." for p<10%, "*" for p<0.05, "**" for p<0.01, and "***" for p<0.001. For compactness, the intercept and the coefficients on the 15 dummy variables are omitted. The level of efforts required for an engagement: like<comment<retweet.

First, the exogenous exclusive variable "isEligible" has strong positive effects on participation, showing that the eligibility restriction does indeed affect endorsers' decisions to participate. In contrast, the other exogenously manipulated variable "price" has no effect on participation. While the higher price level used in our experiment exceeds 91% of linear prices ever used on weituitui, it might not be high enough to make a difference. As we mentioned earlier, while incentive usually increases response rates, it may not work if it's promised rather than prepaid (Cantor et al. 2008; Church 1993). An alternative explanation is that the marginal effect of incentive has already declined to around zero at the lower price level, in line of the common finding that the marginal effect of incentive declines with incentive size (Singer and Ye 2013). This null finding has important implications to marketers, as it suggests that higher pay rates do not necessarily improve response rates. In other words, improving response rates through increasing financial incentive can be a very costly yet inefficient approach. The fact that pay rate has no effect on outcome is consistent with previous findings that incentive has no effect on response quality when payment is not contingent on performance (Singer and Ye 2013).

Second, endorsers with more fans and a higher verified ratio are more likely to participate. One very plausible explanation is that endorsers with a greater number of verified fans derive greater status enhancement from relaying attractive deals than endorsers with fewer verified followers (Toubia and Stephen 2013). An alternative interpretation is that, since fans and verified ratio determine the number of verified fans and hence affect the reward of endorsers, this finding indicates that those who are paid more are more likely to participate. This alternative explanation, however, is at odds with the previous finding that pay rate has no effect on participation. A third possible explanation is that endorsers with more fans and a higher verified ratio log into the platform more frequently and hence are more likely to see and respond to a task. According to the manager of weituitui.com, the majority of endorsers only login to the platform occasionally. Our data show that among the participants in two adjacent weeks, on average, only 32% of them participated consecutively in both weeks. Unfortunately, we cannot check whether the log-in rate is indeed higher for those with more verified followers as we don't have access to the logs of weituitui.com. Hence, we cannot assess the third explanation.

Third, in the outcome equation, the number of fans has a significant (positive) effect on likes, but not on comments or retweets. This finding is consistent with our conjecture that the effect of fans may have smaller effects on comments and retweets than that on likes. The reason is that higher levels of engagement require strong ties, whereas the tie strength between endorsers and their fans decreases with the number of fans (Burke 2011; Roberts et al. 2009; Katona et al. 2011). This finding is also consistent with previous findings that network size has a positive effect on overall influence in information diffusion (Yoganarasimhan 2012) but a negative effect on adoption decisions (Katona et al. 2011). As a side note, verified ratio doesn't seem to have positive effects on likes and retweets, implying that weituitui.com may need to give likes and retweets more weight while calculating this coefficient.

Fourth, endorsers who tweeted more on microblogs and who participated in more tasks in the past are more likely to participate in our tasks, yet are less effective in generating engagements. This finding is consistent with our earlier discussion that endorsers who are less selective tend to be less effective. The variable "qualifiedRatio", defined as the percentage of approved tasks in the past, is often thought to reflect the quality of endorsers. However, we find no significant effects of qualified ratio in either the selection or outcome equation. This finding suggests that qualified ratio might not be a good indicator of quality. Instead of being of higher quality, endorsers with a high qualified ratio might just be more skillful in fulfilling the requirements of advertisers. Since qualified ratio has been widely used as a metric to judge the quality of workers in crowdsourcing services such as Amazon Mechanical Turk (Ipeirotis et al. 2010; Paolacci et al. 2010), our finding suggests that the validity and usefulness of the metric warrants more thorough investigation.

Fifth, endorsers who have registered for a longer time and who have more friends on weituitui.com's internal social network are less likely to participate in a task, but more likely to generate engagements. The opposite effects of these two variables (with some exceptions) in participation and effectiveness is consistent with our reasoning that endorsers who are more embedded into the community tend to be more selective and hence enjoy higher social status, rendering them more effective in generating engagements. "referralReward" and "times" are variables specific to the platform and our experiment design, which are not of interest in this paper, as we focus on variables broadly observable in different social media marketing campaigns.

Finally, all the heterogeneity terms are significant, except for γ for likes. For likes, the small γ is a likely indicator of over-specification. We re-estimate the parameters by forcing γ and τ to be zero in our model for all three types of engagements and find that the results are similar. Therefore, our findings are not an artifact of over-specification. We have also tried a variety of simplified versions of our model, including removing random effects, removing dyad level error terms, and removing all correlations (i.e., estimating selection and outcome equation models separately), and find that our findings are highly robust. Further, we conduct extensive additional robustness checks, such as re-estimate the parameters using richer model specifications and re-estimate the parameters after removing potential outlier in data (e.g., some task with very few participants), and find that our findings remain unchanged.

Observable Effectiveness

In Table 6, many variables have opposite effects on participation and potential outcome. Such a tension intrigues us to study the relative partial effects of the independent variables on the observable engagements. For simplicity, we call such effects the total effects of variables (on observable engagements). To generate a large number of observable engagements, an endorser needs to not only have high potential to generate engagements, but also have a high probability to participate in the campaign. The total effect of a variable on the observable engagements can be computed using equation (9), which represents the percentage change of the engagements w.r.t a unit change in the independent variable. Table 7 summarizes the total effects of the independent variables on observable engagements, computed in two different ways. In the "Population Mean" column, we first compute the total effects for each endorser and then take the average over the entire population. In the "Averaged Observation" column, we first average the characteristics of endorsers over the population, and then compute the total effects for the averaged endorser.

Table 7. Relative Partial Effects on Observable Engagements (Total Effects)

	Population Mean			Averaged Observation		
	likes	**comments**	**retweets**	**likes**	**comments**	**retweets**
Financial Incentive						
price=0.0002	0.085	0.129	0.121	0.086	0.13	0.121
Social Media Fan base						
log(fans)	0.48***	0.209*	0.235**	0.479***	0.207*	0.233**
verifiedRatio	1.756**	2.538***	1.844**	1.749**	2.528***	1.835**
Prior Activity Level						
log(tweetNum)	0.134	-0.209*	-0.277*	0.133	-0.21*	-0.278*
log(taskNum)	0.857***	0.782***	0.596***	0.85***	0.773***	0.587***
qualifiedRatio	0.602	1.203	-0.521	0.603	1.203	-0.521
Community Embeddedness						
regDuration	-9.746***	-7.717***	-6.109***	-9.692***	-7.645***	-6.041***
log(friends)	0.211	-0.008	0.319	0.212	-0.006	0.32
Others						
log(referralReward)	-0.028	-0.107.	-0.084	-0.028	-0.106.	-0.083
times	-0.566	-0.805	-0.324	-0.565	-0.803	-0.321

For majority of variables, the direction of the total effects reported in Table 7 are consistent with that in the participation equation reported in Table 6. Hence, participation is oftentimes the primary driver of observable engagements. Variables for which this holds include fans, verified ratio, task number, and registration duration. As a concrete example, the estimates on task number in Tables 6 and 7 suggests that, though endorsers who have participated in a lot of campaigns have low potential in generating engagements, they are more likely to generate actual engagements, due to their strong willingness to participate. However, participation doesn't always dominate potential. For example, the direction of the total effect of the number of tweets is consistent with its direction in the outcome equation, rather than the selection equation. Given that the effect size of tweet number in the selection equation is small compared to that in the outcome equation, this finding is not surprising. In some cases, the opposite effects in the participation and outcome equations may cancel out in the total effects, such as the total effect of the number of weituitui friends. These findings suggest that neglecting either participation or potential effectiveness in marketing campaigns can result in wrong decisions.

In sum, to improve the effectiveness of paid endorsement campaigns, advertisers can relax eligibility-related task requirements to attract endorsers who are effective but have low willingness to participate (e.g., endorsers who have registered for a long time and have many friends on the paid endorsement platform). In addition, advertisers can also strengthen effort-related task requirements to enforce the quality of the responses from endorsers who have high participation rate but low effectiveness (e.g., endorsers who have participated in a lot of tasks and posted a lot of tweets).

Note that the total effects computed using the "Population Mean" and the "Averaged Observation" methods are very close to each other. The reason is that the Mills ratio, a key component in the approximated likelihood, falls in the linear range (Puhani 2000) for majority of our data points. It's well-known that, for linear function, the average of function equals the function of average.

Discussion

One limitation of this study is that it investigates consumer engagement (likes, comments, and retweets), whereas in practice advertisers are often also interested in additional metrics such as clicks and sales. There is a practical challenge with studying the effectiveness of endorsers in generating clicks and sales on the individual level: clicks and sales are hard to track at that level. Currently, the standard way to track clicks and sales is to use different short URLs in different tweets (even if they are for the same product), such that the source of clicks and sales can be tracked back to the short URLs. This means that clicks and sales can only be monitored at the level of task rather than endorser. More fine-grained tracking techniques are needed to study the effectiveness of individual endorsers in generating clicks and sales.

Another limitation of this study is that the tasks may have interfered with each other, even though we used a unique tweet for each task. There are two possible causes for such interference. First, there might be overlap in two endorsers' fan base. If a fan common to two endorsers saw them endorsing the same product, the fan may end up responding to at most one of the endorser's retweet. Second, as we posted multiple tasks on the same product over time, there may have been a saturation effect if a fan saw the same product endorsed multiple times. While such interference may indeed have depressed the average effectiveness, there is no compelling reason to believe it would have done so differentially in a way that would bias our coefficients measuring the association between effectiveness and specific manipulated factors or measured endorser characteristics.[6]

A third potential limitation is that the exclusive variable (i.e., eligibility) may not be truly exclusive. Though the eligibility constraint was assigned randomly and independently of any endorser trait, the imposed (in)eligibility might conceivably have changed the endorsement behavior (e.g., effort level) of the endorser and hence affect her effectiveness indirectly. For example, ineligible endorsers may exert stronger effort than eligible endorsers in order to be approved, or exert lower effort given that they have lower faith in actually getting paid. In paid retweeting campaigns similar to ours, the only place whether endorsers may show differentiated efforts lies in the composition of the comment included in the retweet, if any. Two metrics that reflect the effort level of an endorser in composing a comment is the length of comment (namely the number of words) and the use of emojis. The former metric is commonly used to measure the effort level of respondents (Singer and Ye 2013). We tested the effects of eligibility on length of comment (usage of emojis) using a Poisson (Probit) model with endorser level random effects, using all regressors in the outcome equation as controls, and found that the effect of eligibility is insignificant. Therefore, the concern that eligibility may have affected the effort level and hence effectiveness is not supported by the data.

Conclusions

Paid endorsement, as an affordable crowd-sourcing approach to social advertising, has gained great popularity among small firms in recent years. However, studies on how to effectively target and incent paid endorsers are absent in the literature. This paper aims at understanding how financial incentive and endorser's characteristics affect their participation and effectiveness. Toward that end, we run a field experiment to spread products on a microblog for three vendors on taobao.com, using one of the largest paid endorsement platforms in China. For identification, we exogenously manipulated the financial incentive and eligibility for participation. In order to analyze the collected panel counting data with self-selection and repeated observations, we propose an approach that can address both problems simultaneously.

The research findings of this paper have important implications to marketers and managers in the area of social media marketing: (1) Increasing the pay rate doesn't necessarily improve the response rate of paid endorsement campaigns. This means advertisers might be better off given priority to other aspects of the campaigns, such as the content of the ad message; (2) It's dangerous to access the quality of endorsers solely

[6] Moreover, the 15 task level dummy variable account for any main effect of saturation on effectiveness. Also, in rare cases, a spammer may participate in both tasks in the same group. This may lead to attribution problem if her fans engage on one of the two retweets on the same product. Fortunately, this doesn't cause any real problem for our analysis, as in such cases both retweets will almost always receive zero engagements, due to the fact that the endorser is a spammer.

based on the observed engagements. Endorsers observed to generate high engagement levels are not necessarily the most effective, but simply be more likely to participate. On the other hand, endorsers observed to generate low engagement levels are not necessarily ineffective, but may simply not be likely to participate. This type of endorsers might have been overlooked by the marketers; (3) The willingness to participate and effectiveness in generating engagements are often at odds with each other. This is so for both observed and unobserved characteristics. Consequently, it is difficult to find endorsers who are both responsive (i.e., likely to participate) and effective. Advertisers should explore ways to relax eligibility-related task requirements to attract endorsers who are effective but not responsive, or to strengthen effort-related task requirements to enforce the effort exerted by endorsers who are responsive but ineffective.

Our work can be extended in a number of directions. First, to better understand the effect of financial incentive, it may be more fruitful to conduct the analysis in a gain vs. loss framework, as prospect theory suggests. Second, it would be useful to study the effectiveness of endorsers in generating clicks and sales if it were possible to track these outcomes at the individual endorser level. In addition, it may be interesting to study the differential performance of products in different categories, such as mass vs. niche products or utilitarian vs hedonic products as these may vary in the status enhancement they provide to endorsers. Finally, the composition of the original message posted by the advertiser may also be worth investigating, as effective copy would need to appeal both to endorsers and to their followers. Here again, the distinction between participation and effectiveness may be essential to generating new, fine-grained insights.

Acknowledgements

The research was partially funded by Penn Lauder CIBER PhD grant and Wharton Baker Center PhD grant.

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