An Empirical Examination of Peer Referrals in Online Crowdfunding

Completed Research Paper

Gordon Burtch
Carlson School of Management
University of Minnesota
gburtch@umn.edu

Anindya Ghose
Stern School of Business
New York University
aghose@stern.nyu.edu

Sunil Wattal
Fox School of Business
Temple University
swattal@temple.edu

Abstract

Observational learning and word-of-mouth are frequently confounded in online settings. Consumers purchase a product, enjoy it, and then refer others. In parallel, referral recipients observe a transmitter’s interaction with the product and draw inferences about product quality. We aim to tease apart these effects using data on 42,000+ peer referrals at a leading crowdfunding platform. Our identification comes from the fact that referral transmitters can choose to conceal their prior contributions from public view, making observational learning impossible. We show that referrals are 30% more effective when the transmitter’s past contributions are publicly visible. Moreover, visible prior contributions drive referral recipients to convert more quickly. Acknowledging the potential endogeneity of the referrer’s decision to conceal contributions, we demonstrate the robustness of our results following propensity score matching and discuss the implications for crowdfunding and WOM referrals.

Keywords: crowdfunding, electronic word of mouth, peer referral, observational learning
Introduction

Word-of-mouth (WOM) has long been touted as an effective method for new customer acquisition. Accordingly, since as early as the 1950s, aspects of this type of WOM have been the subject of scholarly research (Katz and Lazarfeld 1955), yet only in the last decade or two have WOM referrals garnered significant attention from marketers as an alternative to traditional advertising tools. Practitioners have noted that WOM, if managed properly, can offer a cheap, effective approach to new customer acquisition (Dellarocas 2003; Dellarocas 2006). Much of the increased attention paid to WOM in recent years is attributable to the advent and growth of the internet and social media (Trusov et al. 2009). These technological developments have made customer-to-customer communication significantly easier, and thus more prevalent. However, even with this increased attention from practitioners, many nuances of the WOM process remain rather ambiguous, particularly when it comes to the activities and influence of those individuals producing it (Ryu and Feick 2007; Stephen and Lehmann 2009).

Although a number of recent studies have provided clear empirical evidence of the value of electronic WOM over and above other drivers of new customer acquisition (Chen et al. 2011; Trusov et al. 2009; Villanueva et al. 2008), such studies have generally been conducted at an aggregate level of analysis, making it difficult to identify the exact mechanisms that underpin the results. Those few studies that have considered individual-level facets of the WOM process and its outcomes have focused largely on characteristics of the sender-receiver dyad, the product (service) that is targeted, or the recipient (Brown and Reingen 1987; Wangenheim and Bayón 2007). That is, sender-side aspects of the WOM referral process have received relatively less examination to date (Stephen and Lehmann 2009).

Here, we build on existing work by exploring the parallel, often confounded effects of observational learning (OL) and WOM in online social contexts. In so doing, we address a question recently highlighted by Libai et al. (2010) in their review of the WOM literature: “to what degree does observational learning play a role in C2C interactions compared to verbal word of mouth?” The primary issue here is that, in online social contexts, the effects of OL and electronic WOM are difficult to tease apart, particularly when the behavior (e.g., consumption, purchase) of the WOM transmitter is observable to the recipient.

The WOM (referral) transmitter’s prior observable engagement with the product or service may be significantly associated with the recipient’s probability of conversion for multiple reasons. On the one hand, this may drive an OL effect, because the recipient may infer that the transmitter holds some private information about the product or service (see the work of Bikhchandani et al. 1998 for an elaboration on this topic). On the other hand, it may serve as a reflection of the transmitter’s ‘passion’ (intensity of preference) for the product or service, and thus it may reflect the effort the transmitter has put into convincing the target recipient (Biyalogorsky et al. 2001).

Our study addresses the following research questions. First, is WOM more effective when issued by existing customers, compared to non-customers? Second, are those effects increasing in the customers’ intensity of prior engagement with the product or service in question? Third, to what degree are these effects attributable to the WOM message content versus OL? In order to address this last question, we exploit features specific to our study context, which enable any given user to conceal spells of their activities from public view, in a granular, dynamic fashion. While publicly visible records of prior consumption, adoption or engagement can feasibly capture both WOM and OL effects, invisible records, in contrast, can only be associated with a WOM effect.

Our study is situated at one of the world’s largest global online crowdfunding platforms. We employ a unique dataset of impression-level observations associated with more than 42,000 web-based peer

---

1 This aspect is particularly interesting, because it allows us to build on past work (Iyengar et al. 2011), which has inferred that high-volume users have a greater probability of driving new customer acquisition because their extensive use conveys additional information. Here, we can directly identify whether such information is conveyed to a referral recipient.

2 While our total sample includes more than 160,000 referrals, campaign organizers were responsible for approximately three quarters. We exclude such referrals under the presumption that organizers’ contributions toward their own campaigns carry less weight or influence, and that those effects may
referrals, issued by more than 14,000 transmitters. We analyze the efficacy of these WOM referrals subject to variation in the transmitter’s prior, publicly observable and unobservable contributions toward the target campaign. First, ignoring the visibility of prior contributions, we find that, relative to referrals from non-contributing users, those issued by a campaign contributor are 44% more likely to result in the recipient’s conversion. We also find that the efficacy of a peer referral is indeed increasing in the amount of the transmitter’s prior campaign contributions. On average, a 25% increase in the referrer’s prior contribution amount is associated with an approximate 1% increase in the probability of recipient conversion from a referral. Next, seeking to piece apart OL from WOM effects, we compare the influence of visible and concealed prior campaign contributions on the part of the transmitter. Doing so, we find that the effect of visible contributions is much stronger than that of invisible contributions, to a statistically significant degree ($F = 4.37, p < 0.05$). This result provides evidence for the presence of both WOM and OL effects, with OL accounting for approximately 30% of the joint effect.\footnote{This estimate is based on an assumption of linear additivity, as well as the fact that the coefficient associated with the visible dollar contributions is approximately 1.3x larger than the coefficient associated with the invisible dollar contributions.}

Being cognizant that the transmitter’s hiding / revealing decision is potentially endogenous (e.g., perhaps they conceal ‘bad’ contributions and reveal ‘good’ ones), we undertake a set of supplementary analyses, leveraging propensity score matching (PSM). Moreover, we explore the mechanism by which OL and WOM drive increased conversion probabilities. We present evidence of a negative association between transmitters’ observable past contributions and the visit duration of converted users, indicating that observable prior contributions reduce deliberative effort on the part of converted recipients. Interestingly, we find no such relationship for unobservable prior contributions.

Our approach accounts for various sources of unobserved heterogeneity. First, our models address static heterogeneity associated with campaigns, referrers and time by instituting 3-way fixed effects.\footnote{Our dataset unfortunately does not allow us to identify referral recipients across all observations, because we observe their identity only when they contribute funds. This makes the inclusion of recipient fixed effects a challenge. Instead, we focus on a number of important session-related variables (i.e., visitors’ physical location and device form factor) in our estimations to address recipient heterogeneity.} Second, we undertake additional analyses that address the potential endogeneity associated with the transmitter’s hiding / revealing decision, with respect to their prior contributions, using a matching strategy. Third, and last, we undertake a variety of robustness checks, employing alternative estimators, subsamples and data splits. In general, we find that our results are broadly consistent across all of our estimations.

Our findings have important implications, not only for electronic or referral-based WOM, but also for WOM in general. First, a number of recent studies have examined offline settings in which consumer behavior is influenced by that of observable peers, attributing the effects to observational learning or mimicry (McFerran et al. 2010; Tanner et al. 2008), for example. Here, we translate those results to an online context, where it is becoming increasingly common for user behavior to be publicly recorded. Second, pursuant to the above, our results have generalizable implications for all those online contexts in which electronic WOM recipients can observe prior purchasing and consumption behavior of others in their social network (e.g., Last.fm, Spotify, Facebook). What is more, many websites that directly enable WOM now offer explicit, publicly observable indications of the transmitter’s past activities relative to the product or service they are evaluating. On Yelp, one can easily observe whether and how frequently the author of a restaurant review has checked in at a restaurant location, as this information is provided alongside the review. Similarly, Amazon provides ‘verified product reviews’, that confirm the reviewer’s past product purchase.

The remainder of this paper proceeds as follows. In the following section, we review the literature on WOM referrals, signaling and crowdfunding. We then leverage our review and integration of the literature to motivate an econometric model, which we will take to the data. Following that, we describe our study context and the details of our data, before estimating our models. We detail the results of our estimation,
offering our interpretation and discussing the implications for theory and practice. Finally, we conclude with a consideration of the limitations of this work, and offer up a number of potential avenues for future research.

**Literature Review**

**WOM & Peer Referrals**

The WOM literature has looked at the efficacy of WOM as a function of the influence of WOM transmitters and the susceptibility of recipients (Aral and Walker 2012; Forman et al. 2008; Gershoff et al. 2007; Iyengar et al. 2011), transmitter selectivity and motivations in targeting specific recipients (Stephen and Lehmann 2009) and characteristics of the product or service being considered (Chen et al. 2011). Studies have also looked at the roles of monetary incentives, tie strength and brand in driving customers to issue peer referrals (Ryu and Feick 2007), as well as recipients' possible negative reaction to incentivized peer referrals, if they perceive an ulterior motive on the part of the sender (Tuk et al. 2009). More recent work has also examined the longer term value of customers acquired via WOM referral (Schmitt et al. 2011).

Our focus in this particular work is on the distinction between OL and eWOM in the peer referral process in online crowdfunding. We seek to address a key outstanding question posed by Libai et al. (2010): “to what degree does observational learning play a role in C2C interactions compared to verbal word of mouth?” The basic issue here is that WOM referrals in online social settings can result in new customer acquisition for different reasons. First, a web-based peer referral from an existing customer might be more effective than that from a non-customer because an existing customer should be willing to expend greater effort in convincing others. Supporting this notion, Biyalogorsky et al. (2001) argue that customers will engage in product advocacy only after some threshold of satisfaction (delight) is surpassed. Similarly, Godes and Mayzlin (2009) examine the impact of WOM exogenously stimulated amongst customers, compared to that stimulated amongst non-customers. A key premise in their study is the idea that loyal customers will be more willing to advocate a firm’s product. Here, we employ a logical extension to that idea, which is that the degree of effort a customer is willing to expend in advocating a product should be increasing in their degree of loyalty.

Second, a web-based peer referral from an existing customer could also drive increased conversion because of OL. This is true, in particular, when the transmitter’s prior consumption behavior is observable by the recipient. This notion of OL has grown increasingly important in the Internet age, particularly with the advent of social media, because WOM transmitters’ consumption activities are quite often a matter of public record. Crowdfunding campaign contributions provide a prototypical example of this.

Three recent studies have examined the distinctive roles of OL and WOM in online social contexts. First, Li and Wu (2013) studied these mechanisms in relation to Groupon daily deal vouchers. The authors leverage aggregate panel data on voucher sales and show that they are jointly affected by both OL, resulting from the publicized total count of past voucher purchases, and WOM, resulting from Facebook likes. The authors report that Facebook WOM has a stronger effect than OL. Next, Liu et al. (2013) study the effects of WOM and OL on rates of stock market participation in China, at the province level. Those authors report that both mechanisms of social learning impact stock market participation. Further, they show that WOM effects are stronger in the presence of greater social interaction (mobile phone and internet use), whereas OL effects are stronger in the presence of greater passive communication about stock market performance (TV and newspaper coverage).

Third, and last, Chen et al. (2011) study the joint effects of WOM (product ratings) and OL (product recommendations, which are based on others’ purchases) on aggregate camera sales at Amazon.com. The authors exploit a natural experiment, wherein product recommendations were disabled on Amazon for a number of months, and then reintroduced. The authors report that WOM and OL have different impacts on sales. Whereas negative WOM has a stronger effect than positive WOM, the same is not true of OL. Although positive signals from OL (i.e., more recommendations) have a significant impact on sales, negative signals (i.e., a lack of recommendations) do not. Moreover, these authors report that the volume of WOM complements OL, in that the effects of OL grow stronger in the presence of more product reviews.
Our work differs from, and builds upon, these recent studies in multiple respects. First, past studies of these mechanisms have employed aggregate level data on the product or service being consumed (e.g., “as more WOM manifests in aggregate, or as publicly observable popularity measures shift, how do product sales change?”). For this reason, those studies have not been able to identify or quantify the individual effects in question. Instead, they have considered aggregate associations, which are inherently noisy and challenging to identify.

Further, the WOM that has generally been studied in the past has been quite varied in nature. Some scholars have operationalized this in terms of Facebook likes, suggesting that when one user “likes” a product online, their friends observe this on Facebook, and take it as evidence of approval or preference. Other scholars have operationalized WOM in terms of online review volumes and valences. In our study, we focus upon WOM in the form of direct peer referrals, where the transmitting individual is known to have brought the crowdfunding campaign to the recipient’s attention. To our knowledge, our study is the first to consider peer referrals and OL in tandem.

Third, and last, our work considers WOM and OL in a novel research context, crowdfunding, which is an important phenomenon in its own right. Our work is the first to study the dual roles of OL and WOM in crowdfunding campaign contributions, shedding light on the role of social influence in driving campaign contributions. In the next section, we detail the nascent body of work on crowdfunding, placing a particular focus on the role of customer-to-customer (C2C) communication, social networks and social media. Importantly, we highlight the dearth of research on the individual-level dynamics of these phenomena and factors in the crowdfunding process.

**Crowdfunding**

Crowdfunding has been defined as a collective effort by individuals who network and pool their money via the Internet, to invest in or support the efforts of others (Ordanini et al. 2010). These activities are facilitated by online crowdfunding platforms, of which there are now more than 450 in operation around the world (Massolution 2013). In fact, the crowdfunding industry as a whole is growing at an exponential rate. Massolution’s recent industry report indicates that crowdfunding helped individuals and organizations to raise more than $2.7B in 2012, up 81% from the year prior, and it is expected to surpass $5.1B in 2013. Crowdfunding platforms come in four flavors, including donation-based, lending-based, reward-based and equity-based (Burtch et al. 2014a). Over the last few years there have been a number of studies on the subject. Recent examples of research include the work by Burtch et al. (2014c), which considers the effects of privacy control provision on crowdfunder behavior, as well as the work of Herzenstein and his colleagues, who study herding behavior and aspects of a borrower’s pitch construction (Herzenstein et al. 2011a; Herzenstein et al. 2011b).

Most relevant to the present study, however, is research touching on social networks in crowdfunding. Unfortunately, such work has been quite limited to date. Nonetheless, WOM is an integral component of the crowdfunding process, which makes crowdfunding platforms the ideal context for the study of WOM referrals. Of course, scholars have shown the importance of a fundraiser’s social network when it comes to achieving success on crowdfunding platforms. First, the social network can act as a signal of the organizer’s quality, reducing uncertainty on the part of contributors (Lin et al. 2013). Second, crowdfunding campaign organizers’ social networks often form the core body of contributors (Agarwal et al. 2011). Third, and perhaps most importantly, having access to a larger social network enables campaign organizers to get the word out more easily, enabling buzz and awareness for their campaign (Burtch et al. 2013a; Mollick 2014). What is more, Mollick notes that much of the value derived from social networks may extend from a Matthew Effect – a social multiplier effect – wherein first-degree connections, after contributing, may become brand evangelists, reaching out to second-degree connections, etc. to aid in the fundraising process.

Given the apparent importance of both WOM and OL in the crowdfunding context, it is notable that no prior work has explored it at an individual-level. We surmise that this has been due to data limitations. Each of the studies noted above reports findings that are based either on an aggregate evaluation of campaign-level outcomes or on indirect inference using proxy measures (e.g., physical distance). This is likely because peer-to-peer interaction is typically not made publicly observable, thus it is a challenge to study. Here, because we have data on activities going on under the hood (i.e., referral transmission, concealed behavior), we are able to shed light on these phenomena. This is important, because the
dynamics and mechanisms underlying crowdfunder WOM referrals have important implications for platform policy, purveyor marketing activities, and campaign organizer strategy. What is more, these aspects have important implications for WOM marketing in general.

**Methods**

**Study Context & Data**

Our study focuses on one of the world’s largest global crowdfunding platforms. The platform enables anyone, in any location, to raise money for a project, venture or cause. The site is highly trafficked, entertaining tens of thousands of visitors per day, and facilitating millions of dollars in campaign contributions each month. Since being founded approximately five years ago, the platform has attracted more than 1 million registered users from more than 190 countries, and it has hosted tens of thousands of campaigns. When a campaign organizer submits their project to the marketplace, they must define a number of campaign characteristics, such as the topic category, the target budget, the duration of the campaign, etc. Visitors to the website are able to browse campaigns or to filter them based on attributes, such as location or category. Any time a visitor accesses a campaign URL the platform purveyor records the details of the session. Amongst others, these data points include the source domain from which the user arrived, the campaign identifier, how long the user remained at the campaign page, whether the session resulted in the visitor contributing funds and, if so, their user id.

Visitors may also arrive directly to a campaign URL as a result of a web-based referral from another user. The referring user’s ID is tracked using a parameter that is inserted into the URL when it is initially generated (either via the keyboard copy command, or using the built-in share tool on the platform website). When the referred user clicks on the hyperlink, if such a parameter is present, it is extracted by the website purveyor and recorded along with other session details. Figure 1 below provides a screenshot of published campaign contribution records on the website, as well as a depiction of the sharing mechanism.

![Figure 1. Contribution Records (Left) & Share Tool Examples (Right)](image)

5 If the user copies the campaign URL from their browser address bar, the parameter indicating their user ID will automatically be included. Similarly, if the user generates a Tweet, e-mail, or code for a website widget, the parameter containing their user ID is automatically included. Further, if the user is not logged in when they attempt to use the sharing tool, they are prompted to do so by a pop-up window.
In the backers list, we can see examples of anonymous contributions (invisible), as well as identified contributions (visible). In the sharing examples, the 6-digit number reflects the WOM referral sender's user ID. It is notable that the platform purveyor has recently taken note of the importance of WOM referrals in crowdfunding. They have recently taken steps to provide campaign organizers with dashboard metrics indicating the frequency and volume of peer referrals taking place to their campaign, as well as indications of which users are driving the greatest volume of referrals. These metrics enable and guide campaign organizers in managing their marketing efforts.

Our dataset includes proprietary information, supplied by the website purveyor, associated with all campaigns, users and visits over a 3 month period, spanning December of 2012 through February of 2013. The data comprises more than 42,000 campaign URL impressions. Table 1 provides descriptive statistics for each of our variables, noted and defined in the prior section. The baseline probability of conversion for a user arriving via a WOM referral is approximately 18%. We observe that transmitters have contributed funds, prior to issuing their referral, approximately 38% of the time. Further, in general, within the same campaign, we observe that referral transmitters are generally quite consistent in their revealing and hiding behavior (i.e., they reveal all of their contributions, or they conceal all of their contributions, most of the time).

We see a mix of revealing and hiding on the part of the transmitter in approximately ~1% of observations. WOM referral conversion is significantly correlated with the different variables noted in our model formulation section, including the referrers’ past contribution behavior (with respect to the target campaign), visitor proximity to the campaign and visitors’ device form factor (i.e., mobile vs. desktop). We observe a negative correlation between mobile device usage and conversion (rho = -0.03, p < 0.001), as well as a positive correlation between the referrer’s prior contributions, both in terms of the binary indicator of the action (rho = 0.24, p < 0.001), as well as the continuous indicator of the amount (rho = 0.01, p < 0.05).

We also examined how common it actually is for crowdfunders to look at the list of prior contributors for a given campaign, before contributing. We did so because this behavior is a key premise underlying our models and analyses; if crowdfunders do not look at this information, then it is impossible for observable signals of referral transmitters’ prior engagement to have an influence on the recipient. To examine this, we collected additional data from the platform purveyor on within-session user-navigation patterns. Specifically, we collected additional data about the last campaign tab viewed during the web sessions of approximately 145,000 campaign visitors, before they proceeded elsewhere (i.e., into the campaign contribution flow or exiting). We found that more than 40,000 of those visitors examined the list of
funders before navigating elsewhere. This proportion (~28%) provides a lower bound on the prevalence of this behavior because some proportion of the other 72% of visits would also have involved navigation to the list of prior funders, at some earlier point in the session – we simply do not observe this. We can therefore safely conclude that there is a clear potential influence from the actions of prior contributors on later contributors.

**Hypotheses & Model Formulation**

Our key variables of interest in this estimation are whether the sender of the referral has previously contributed to the target campaign, the amount of money the sender has previously contributed to the target campaign, and the visible and invisible amounts of money the sender has previously contributed to the target campaign. Our outcomes of interest are the probability of recipient conversion, and the dollar amount of recipient contributions toward the target campaign. These variables reflect the efficacy of a referral, and we anticipate that each will be increasing in the amount and visibility of transmitters’ prior campaign contributions. Before proceeding to our model, we propose a set of formal hypotheses, capturing our anticipated relationships.

Our first hypothesis pertains to the continuous nature of prior contributions. Specifically, we expect that increasing amounts of prior contribution by referral transmitters, toward the target campaign, will be associated with increased likelihood of recipient conversion. For example, the transmitter’s prior contribution amount may serve as a benchmark for the recipient’s own contribution. Alternatively, the amount may provide the recipient with an indication of the quality of the campaign. Moreover, even if the prior contribution was concealed, larger contributions are expected to reflect greater enthusiasm or support for the campaign, and thus increased effort on the part of the transmitter. Bearing this in mind, we propose our first hypothesis.

**H1: Referrals transmitted by individuals who have previously contributed to the target campaign will be more likely to result in recipient conversion when those prior contributions were made in larger amounts.**

Next, we consider the distinction between revealed and concealed prior contributions by referral transmitters. Our basic expectation here is that revealed prior contributions will have a stronger effect on recipient conversion than concealed prior contributions. While concealed prior contributions are expected to have a significant, positive effect on recipient conversion, because such contributions are expected to reflect transmitter enthusiasm and effort, revealed prior contributions should have an even stronger effect, because OL becomes possible. We formalize this expectation in our second hypothesis.

**H2: Referrals transmitted by individuals who have previously contributed to the target campaign will be more likely to result in recipient conversion when those prior contributions were made public.**

Each of our key independent variables is dynamic, in that the timing of contribution determines whether a particular referral recipient was able to observe a prior contribution by the transmitter. Further, repeated contributions on the part of the transmitter are possible, over time, thus the dollar amounts of observable and unobservable contributions can vary continuously, increasing monotonically over time. We refer to the above variables, respectively, as PastPledger, which is a binary indicator, PastPledgeAmount, PastPledgeVisible and PastPledgeInvisible, where the latter three variables are treated as continuous, dollar amounts. We employ these variables across multiple estimations, focusing only on those referral observations in which the sender was not formally affiliated with the campaign (i.e., an organizer). We begin by estimating the effect of PastPledger, ignoring the visibility of prior contributions for the moment.

We then proceed to estimate the effect of the continuous PastPledgeAmount, to assess whether any effects are in fact increasing in the size of prior contributions by the transmitter. Finally, we seek to piece apart the effects of WOM and OL, estimating the parallel effects of PastPledgeVisible and PastPledgeInvisible.
In our primary estimation, we model the dollar variables in terms of logs. This decision was motivated by our initial observation of diminishing marginal returns in our exploratory analysis.6

Our modeling approach is also motivated by prior research in the crowdfunding literature. Based on that work, we begin by incorporating a number of dynamic controls pertaining to the campaign funding status. These include the amount raised by the campaign as of the time of observation, as well as the number of days the campaign had been in the funding process. Although past work has varied in the operationalization of these variables (e.g., log transforms), here, we employ untransformed measures, presuming a linear relationship to the probability of conversion. However, we did also explore the robustness of our results to this assumption finding no material differences in our key coefficient estimates. We refer to our two funding status variables as Balance and Duration, respectively.7

Given the granularity of our data, we are also capable of controlling for other session- or recipient-related variables that are likely to have a strong influence on the probability of conversion taking place. Specifically, we control for the device – mobile or desktop/laptop - the user is employing upon their arrival, presuming that a mobile user will be much less likely to proceed through to a campaign contribution because of limitations in the user interface. Recent research has demonstrated differences in user behavior between mobile and desktop internet, especially when it comes to search costs of evaluating offers and the cognitive costs of processing information (Ghose et al. 2013). We also control for the user’s location, which is identified based on their Internet browser settings, relative to the location of the target campaign. We do so because a number of prior studies have noted the importance of physical proximity in crowdfunding contributions, which may extend from locale specific benefits (e.g., community crowdfunding for urban development), familiarity (Burtch et al. 2014b), social connection (Agarwal et al. 2011), or a home bias (Lin and Viswanathan 2013). Both variables are operationalized as binary indicators. The first is an indicator of whether the user is on a mobile device, Mobile, and the second is a binary indicator of whether the user is located in the same country as the campaign, SameCountry.

Our estimation also incorporates a series of fixed effects, instituted via a combination of a within-transformation and dummy terms. We include fixed effects for each campaign-referrer combination – i.e., a form of spell fixed effects (Andrews et al. 2006). Further, we incorporate time period dummy effects, in order to control for unobservable shocks to demand, such as platform purveyor marketing efforts, overall societal interest in the crowdfunding phenomenon, or any seasonal trends. Equation 1, presented below, captures our model. In this equation referral recipients are indexed by $i$, referral transmitters are indexed by $j$, campaigns are indexed by $q$ and time is indexed by $t$.

$$Conversion_{ijqt} = \beta_1 \ast PastPledger_{ijqt} + \beta_2 \ast Mobile_{ijqt} + \beta_3 \ast SameCountry_{ijqt} + \beta_4 \ast Balance_{ijqt} + \beta_5 \ast Duration_{ijqt} + \phi_j + \gamma_q + \lambda_t + \epsilon_{ijqt}$$

In subsequent analyses, we replace PastPledger with Log(PastPledgeAmount), our logged continuous measure of the amount of money pledged by the transmitter. Subsequent to our main analyses, we also consider a number of moderating effects related to observable indications of the transmitter’s potential relationship.

6 We began by first estimating the effect of the untransformed dollar amount on conversion probability, and we then incorporated a squared term. We found evidence of a significant and positive main effect, as well as a significant and negative higher order term, of lesser magnitude, consistent with a concave relationship.

7 We also explored inclusion of a variable capturing daily web traffic to the campaign URL. This was intended to capture temporal variation in campaign or organizer popularity, over time. This variable produced a significant, positive effect. However, our other coefficient estimates remained quite stable in the estimation, maintaining the significant differential between the effects of visible and invisible prior contributions. As such, we exclude the popularity measure from our estimations for the sake of simplicity.

8 As noted previously, our models do not incorporate recipient fixed effects because we are unable to comprehensively identify recipients across our sample, particularly in those cases where the recipient did not identify himself or herself (i.e., when he or she was not converted). Accordingly, we rely primarily on our controls for device platform and location to account recipient heterogeneity.
ulterior motives in issuing the referral. Specifically, these moderators pertain to whether the transmitter opted to claim a reward for their contribution, as well as whether the campaign in question is required to hit its funding target in order for the organizer to receive funds (i.e., fixed vs. flexible funding). Next, we replace \( \text{Log(PastPledgeAmount)} \) with \( \text{Log(PastPledgeVisible)} \) and \( \text{Log(PastPledgeInvisible)} \), in an effort to identify the effect of OL, as described previously. In these analyses, a positive coefficient associated with \( \text{Log(PastPledgeAmount)} \) would be taken as evidence in support of hypothesis 1. Further, if we find a statistically significant difference in the coefficients associated with \( \text{Log(PastPledgeVisible)} \) and \( \text{Log(PastPledgeInvisible)} \), with that of \( \text{Log(PastPledgeVisible)} \) being the larger of the two, this would be taken as evidence in support of our second hypothesis.

Following the above analyses, we consider transaction durations, exploring the association between WOM, OL and the time that converted recipients spend deliberating over their contribution to a campaign (i.e., time spent at the URL), \text{VisitLength}. We then also report on an additional analysis, wherein we address the potential endogeneity of the referral transmitters' past hiding decisions. Specifically, we re-estimate our focal model – i.e., that incorporating logged visible and invisible prior contributions - using PSM. We construct our estimation sample through exact (single) nearest neighbor matching of referral observations, based on their propensity to receive ‘treatment’ as a function of various characteristics associated with the referral, the referral transmitter, the referral transmitter’s past contribution behavior and the target campaign. The ‘treatment’ in this case is the proportion of prior contribution dollars concealed by the transmitter, rounded to 0 or 1.

**Results**

**Main Regression Results**

We begin by estimating the simple effect of a WOM referral sender having contributed funds previously to the target campaign (whether or not that contribution was made public). This estimation is presented in column 1 of Table 2, below. Here, we can see that there is a quite large, significantly positive effect on the probability of conversion from a WOM referral when the sender has contributed to the target campaign, prior to issuing the referral. In fact, the estimate indicates that the probability of conversion increases by a staggering 44\%\textsuperscript{10}. Further, looking at columns 2 and 3 in the same table, we see that the effect also varies with the amount of the sender’s prior contributions. A 25% increase in the amount of the sender’s prior contributions (i.e., a $50 increase), is associated with a 1% increase in the probability of recipient conversion. This result is notably consistent with the findings of past research on WOM, by Iyengar et al. (2011), which found that prescribing physicians are more influential in converting other physicians when they prescribe in higher volumes.

When we move to column 3, to consider the differential effect between observable and unobservable prior contributions made by the referral sender, toward the target campaign, we again see the anticipated effects. Both visible and invisible prior contributions have significant positive effects. This supports the claim that the observable indicators of senders’ prior campaign contributions simultaneously reflect their ability or effort to persuade referral recipients to convert and their mere visibility drives the recipient to convert, likely due to an observational learning effect. Further, we see that the effect of visible prior contributions is significantly stronger than that of unobservable prior contributions (\( F = 4.37, p < 0.05 \)), with an effect that is about 1.3x stronger. This suggests that approximately 30% of the effect of observable prior contributions is attributable to observational learning, deriving from the recipient's passive observation of the referrers' prior behavior.

Next, we consider an anticipated log-linear relationship between the amount previously contributed by a WOM referral sender, and the amount then contributed by a recipient. Looking at the results from our re-estimation, in Table 3, where we have substituted the log transformed dollar amount contributed by the

\[ ~12.5\% \text{ of our observations involved a referral transmitter who concealed a fraction of their prior contributions (i.e., } 0 < x < 100). \]

\[ ^{10} \text{ Note: this coefficient estimate remains stable when the various controls are excluded.} \]
recipient in place of a binary indicator of contribution, we again observe a significant positive relationship.

Further, we again see that the effect of publicly observable prior contributions is stronger than that of unobservable prior contributions. That being said, the differential is actually more pronounced in this case. Specifically, we see that i) a 10% increase in the observable amount contributed by the referral sender is associated with a 4.2% increase in the amount contributed by the recipient, and ii) a 10% increase in unobservable contributions is associated with a 2.8% increase in recipient contribution. Again, the larger effect from observable referrer contributions is consistent with our expectation.

<table>
<thead>
<tr>
<th>Table 2. Regression Results: Recipient Conversion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explanatory Variable</td>
</tr>
<tr>
<td>----------------------</td>
</tr>
<tr>
<td>PastPledger</td>
</tr>
<tr>
<td>Log(PastPledgeAmount)</td>
</tr>
<tr>
<td>Log(PastPledgeVisible)</td>
</tr>
<tr>
<td>Log(PastPledgeInvisible)</td>
</tr>
<tr>
<td>Mobile</td>
</tr>
<tr>
<td>SameCountry</td>
</tr>
<tr>
<td>Duration</td>
</tr>
<tr>
<td>Balance</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Within R-square</td>
</tr>
<tr>
<td>F-stat</td>
</tr>
</tbody>
</table>

Notes: *** p < 0.001, * p < 0.05. Robust standard errors in brackets for coefficients, degrees of freedom for test statistics. Estimates of time effects excluded for sake of brevity. The difference between coefficients associated with visible and invisible prior referrer pledges is statistically significant: $F(1, 21689) = 4.46, p < 0.04$.

<table>
<thead>
<tr>
<th>Table 3. Regression Results: Recipient Contribution Amount (S’s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explanatory Variable</td>
</tr>
<tr>
<td>----------------------</td>
</tr>
<tr>
<td>PastPledger</td>
</tr>
<tr>
<td>Log(PastPledgeAmount)</td>
</tr>
<tr>
<td>Log(PastPledgeVisible)</td>
</tr>
<tr>
<td>Log(PastPledgeInvisible)</td>
</tr>
<tr>
<td>Mobile</td>
</tr>
<tr>
<td>SameCountry</td>
</tr>
<tr>
<td>Duration</td>
</tr>
<tr>
<td>Balance</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Within R-square</td>
</tr>
<tr>
<td>F-stat</td>
</tr>
</tbody>
</table>

Notes: *** p < 0.001, ** p < 0.01. Robust standard errors in brackets for coefficients, degrees of freedom for test statistics. Estimates of time effects excluded for sake of brevity.
Having established the effect of observable prior contributions by referral transmitters, we next considered another variable that is of particular interest. We examined the relationship between the sender’s prior contributions and the duration of time a recipient spends at viewing the target campaign URL before contributing. We did so in order to understand how, and to what degree, referral sender’s prior engagement with a campaign is associated with the effort expended by recipients in evaluating those campaigns. We estimated our model of visit durations employing a Poisson estimator with three-way fixed effects. We employ this estimator primarily because our visit duration variable follows a power distribution with a mass around zero. Further, the variable is comprised of non-negative integer values. We opt here for a Poisson Fixed Effects estimator, rather than a Negative Binomial estimator, because the latter can only be implemented in a consistent manner by including vectors of dummy variables associated with each unit – i.e., campaign, referrer and time dummies (Allison and Waterman 2002). Given the large volume of referrers and campaigns in our sample, this would be computationally intractable. We provide a histogram of VisitDuration in Figure 2. It should also be noted that, in this estimation, we employ only those observations where the referral recipient ultimately chose to contribute some strictly positive amount of money to the target campaign.

We do so because contributing recipients will spend greater amounts of time at a campaign than non-contributing recipients, simply because of the time it takes to complete the contribution process (UI interaction), and not because of any differences in deliberative effort. In focusing only on converted referral recipients, we can look to identify whether there are differences in the amount of time such users spend considering a campaign, before finalizing their contribution action, and we can then assess whether those differences are a function of the sender’s prior contributions.

Figure 2. Histogram of Visit Durations

Our results are presented in Table 4. We once again see a significant effect on visit durations from a binary indicator of the sender’s prior contributions, the amount of that contribution, and the amount of observable prior contributions. Interestingly, we do not see a significant effect from unobservable prior contributions. This result indicates that the impact of a transmitter’s prior contributions on a recipient’s visit duration operates primarily, if not exclusively, through OL. All significant effects are negative in this case, which indicates that WOM referrals received from individuals that have themselves contributed to the target campaign result in less deliberation on the part of recipients. This suggests in turn that recipients face less uncertainty in their decision in the presence of observable contributions by transmitters. In particular, we find that a 10% increase the size of a sender’s observable prior contributions is associated with a 0.7% decrease in the amount of time a converted recipient spends at a campaign URL before completing their contribution transaction.

Repeating our estimation employing OLS, as well as OLS with a log-transformed dependent variable produces consistent results.
Robustness Checks

The referral transmitter’s initial decision to reveal or conceal their campaign contributions may very well be endogenous. Accordingly, we undertook an analysis intended to explicitly address this possibility. In an ideal scenario, we would address this issue by either a) exogenously manipulating the recipient’s ability to observe a transmitter’s past contributions, or b) identifying a valid instrument for the transmitter’s hiding decision. However, because we have no such instrument, and we clearly do not have the means to manipulate the recipient’s visibility of prior transactions, we employ alternative means, in the form of propensity score matching (Abadie and Imbens 2006; Rosenbaum and Rubin 1983), wherein for every treated observation, we identify a matched observation (i.e., same characteristics) that was not treated, in order to create a quasi-experimental setup.

We use the term ‘treatment’ loosely, here, defining this as a binary indicator of whether a referral was issued by a transmitter who chose to conceal the ‘majority’ of their prior campaign contributions (i.e., we round the proportion of concealed prior contributions to 1 or 0). We match observations on a variety of observables, including some dynamic sources of heterogeneity associated with the referral transmitter (i.e., marketplace tenure, prior campaign pledge amount, reward / perk claiming). We perform the matching process with a first stage Probit estimation, followed by a one-to-one propensity score matching technique. We are able to obtain matches with common support for exactly 641 observations, resulting in a total matched sample size of 1,282 observations. A non-parametric test of distributional equivalence, the Kolgomorov–Smirnov test, is easily rejected in the unmatched sample (p < 0.001), yet cannot be rejected in the matched sample (p = 0.998). To illustrate this graphically, we provide two Kernel density plots in Figures 3, depicting propensity score distributions of the treatment and control groups pre- and post-matching.

Using the matched sample, we repeated our primary set of estimations. The most important of these estimations was that in which we divided the transmitter’s prior contributions into revealed and concealed prior contributions. Doing so, we observed the exact same effects reported previously. Both revealed and concealed prior contributions have significant positive effects on the probability of recipient conversion, with the effect of the former being much larger, to a statistically significant degree. Given the consistency of our results, we feel confident that the transmitter’s decision to reveal or conceal their contributions does not introduce a source of bias into our estimations.
We examined the robustness of our results in a few other respects as well. First, we considered the possibility that an unobservable selection effect might be at play, wherein referrals that result in conversions might be systematically different from referrals that do not. First, the referrals may be different in terms of the transmitter’s reasons for issuing them. For example, it may be that referrals that result in conversions are those that are framed as solicitations for contribution, while those that do not are really just efforts to communicate interesting information. Second, the referrals may vary systematically in terms of the transmitter’s selectivity around which users they target. Past work has shown that referrals are more likely to result in conversion when they are sent in a targeted fashion (Aral and Walker 2011). Accordingly, successful referrals might simply be those that are sent in a more targeted manner.

In order to address the first possibility, we undertook a subsample analysis, in which we limited our estimation only to those observations in which the sender of the referral contributed money to the target campaign at some point within our period of observation. Importantly, all such senders should be relatively homogenous in their motivations (i.e., soliciting donations from others, rather than communicating out of interest), yet identification remains possible because of variation in the timing of the sender’s contribution, whether before or after the referral is issued. Repeating our estimation on this subsample of approximately 17,000 referrals, we found estimates that were almost identical to those reported in our earlier estimations.

To address the second possibility, we temporarily excluded those observations where the referral recipient arrived at the campaign URL from an e-mail related source domain (e.g., Yahoo! mail, Live Mail). In addition, we exclude those observations where a source domain was not determinable, as an unknown portion of such observations will likely include email referrals as well. Assuming that e-mail referrals are inherently more targeted than other types of referrals (e.g., those issued via social media), we drop the former from this analysis and examine whether our results remain consistent in their absence. In doing so, we effectively rule out targeting versus broadcasting as an explanation for our findings. We are left with approximately 24,000 observations after the removal of e-mail referrals. Our estimation results once again indicated that our coefficient estimates were not unduly influenced by selective referral behavior.

Another possible explanation for our results that we considered was that they are simply due to homophily (Aral 2011; Manski 1993). This would be the case if all individuals who contribute funds have an inherently greater, shared preference for crowdfunding. If this were true, then we might simply be observing a positive correlation in behaviors amongst similar individuals (i.e., “birds of a feather flock together”). However, our results contradict this suggestion, for a few reasons. First, if homophily were a valid explanation for the results we have observed, we would not expect to see any differences in the influence of referrals issued by individuals who had previously made observable prior contributions, rather than unobservable ones, yet we do. Second, the aforementioned subsample analysis of only those
referrals that were issued by contributing referrers (either pre- or post-referral) should not have produced significant effects if homophily were the primary explanation, yet, again, they did. At a minimum, we would expect to see reduced effect sizes in the latter case but even this was not observed.

**Discussion & Limitations**

Our results indicate that WOM and OL have distinct, significant effects, though WOM is the larger of the two. Further, our results suggest that the effects of both WOM and OL are increasing in the degree of prior engagement with the campaign, on the part of the referral transmitter. Our finding of both WOM and OL effects, and the relative impact of each, suggests that marketers and platform purveyors should attend to both when deriving their marketing strategy. Indeed, our findings indicate that, at least in this crowdfunding context, the WOM itself may be the more important driver of new customer acquisition when it comes to campaign referrals, but OL effects are quite large and should not be ignored. Our results suggest that crowdfunding campaign organizers would do well to encourage referrals amongst their existing supporters who have made public contributions. Moreover, some leading crowdfunding platforms have recently introduced campaign referral contests. Our findings indicate that it might be fruitful to incentivize public contributions amongst transmitters and recipients as part of the design of those contests.

Our analyses of converted recipient visit durations also indicate that the OL effect operates in large part by reducing recipients’ deliberative effort, but this does not appear to be the case for the content or persuasiveness of the WOM content. This result sheds some light on the decision-making process of referral recipients, as it indicates the importance of WOM transmitters’ first putting their money where their mouths are, as a show of objective support for the product.

Given the largely social nature of many online platforms today, the visibility of user behaviors is growing increasingly common. Platform designers would do well to incorporate features that allow recognition for user engagement, to offer users incentives to make their activities public, and to then target those users who follow through on said public actions in large quantities. Thus, these findings indicate that referral-based WOM marketing strategies would derive the greatest benefit if conducted via highly engaged customers or users, in contexts where that engagement is publicly observable to peers, and where those customers or users make a point of publicizing their consumption activity. Although transmitter’s probability of converting others grows in the presence of observable past engagement, transmitters may not always being inclined to publicize that information. For example, it may be that more experienced users become increasingly strategic in their revealing and hiding of contributions as they grow more familiar with the marketplace (this is one reason why we matched our sample on refererrer tenure, in the PSM analysis). Alternatively, some users may be relatively more concerned about their privacy. As such, future work can look at the determinants of publicizing behavior, and how best to encourage the revelation of consumer activity.

It is likely that the effect of OL we report here is therefore moderated by sender characteristics. That is, just as McFerran et al. (2010) note that social influence between individuals in terms of observed food consumption volumes is moderated by the observed others’ body type, here, we might expect to see that the influence from observed prior contribution is moderated by the recipients’ familiarity or expertise in the campaign subject area, or by the transmitter’s wealth. Future work might therefore consider the moderating role of referral transmitter and recipient characteristics.

Our study is of course also subject to a number of limitations. First, we do not observe users who ignore the referral and do not click-through to the campaign URL; rather, we only observe what happens after the recipient decides to click through. As a result, our estimates do not capture how prior engagement on the part of the referrer impacts the initial decision of referral recipients to click through. That being said, we would argue that this does not necessarily invalidate our results. Indeed, it is likely that our results are simply conservative estimates, given that many referral recipients likely fail to click through prior to observing the sender’s prior engagement with the campaign (i.e., they might have done so if they had observed an indication of the transmitter’s prior behavior). Further, the persuasive effort associated with such referrals is likely to be systematically lower, and most likely associated with those referrals issued by less committed senders. Regardless, future work would do well to examine the initial stage of the WOM
referral by tracking sharing activity explicitly, rather than focusing estimations solely on those recipients who chose to act on the referral by clicking through on the provided URL.

Our analysis is also constrained by our inability to estimate the baseline effect of a referral, compared to an organic campaign arrival. While this would be a useful piece of information to have, it is a challenge for us to identify, given the significant likelihood that a selection effect would be at play (Stephen and Lehmann 2009). Indeed, it is well established at this point that WOM referral senders are highly selective in terms of who they choose to target with their referrals. Accordingly, future work can explore this aspect of the referral process, employing field randomization in the delivery of referrals or undertaking a lab experiment.

Lastly, it is worth considering the generalizability of our findings. There are a number of reasons why we might expect our findings to extend to more traditional purchase contexts. Entrepreneurs who are looking to implement new products and services are often the source of reward-based crowdfunding campaigns. Accordingly, the decision to support a campaign by making contributions has many direct parallels to product evaluation and purchase. Indeed, in many instances, contributors are promised early access to the product or service being developed in exchange for their contribution. Consider the example of the Oculus Rift Virtual Reality headset, an item that was initially crowdfunded on Kickstarter. The vast majority of the funds obtained in that crowdfunding campaign were attributable to individuals who were interested in claiming development kits.12

It is also notable that a number of past studies have studied WOM and OL in contexts involving charitable donation and public good contributions. Accordingly, results pertaining to those campaigns that do not involve traditional entrepreneurial activities nonetheless remain relevant to the study of WOM and OL. Consider the recent work by Stephen and Galak (2012), who examine the role of WOM in pro-social lending, reporting on a study of the effects of social media buzz on lending activity at Kiva.org. Similarly, consider the work of James Andreoni (2006), who discusses the role played by prominent lead donors in charitable fundraising. He argues that such donors provide a signal of the charity’s quality, and thus facilitate subsequent donations through observational learning. Bearing the above in mind, these results are broadly relevant to the WOM literature, given that it has traditionally touched on a variety of transaction contexts.

Conclusion

A number of alternative avenues exist for future work. It would seem prudent for future work to explore various types of sender engagement, prior to referral. Here, we have only focused on prior campaign contributions in crowdfunding. Future work could consider various other forms of engagement, such as a shared-interest or personal stake in the cause, or frequent communication around the campaign with others (e.g., posted comments, messages). As well, a number of other factors related to the visibility of the referrer’s engagement are likely to play an important role in the WOM referral process. This is increasingly important, given that many online platforms and venues now enable users to conceal or reveal their identity and activities in a very granular, dynamic fashion. As an example, it is notable that we have only looked at the difference between prior contributions that have been obfuscated in some way (e.g., identity was hidden or amount), it is possible that the two types of obfuscation have different impacts on the recipient’s response to a referral.

Our work therefore represents only a first step toward understanding the joint roles of observable indicators of WOM referer commitment, and the patterns of WOM referral within crowdfunding platforms. Future work can help illuminate these issues further, thereby aiding marketers and stakeholders in crowdfunding by informing platform design and strategy. It is our hope that our work can guide future work in that regard.

References


