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Acquiring Customers via Word-of-Mouth Referrals: A Virtuous Strategy?

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Report Summary

Evidence suggests that customers acquired through seeded word-of-mouth (WOM) campaigns or referral programs have higher margin and lower churn probability than customers acquired in other ways. However, the success of such strategies also depends on the extent to which these customers spread the word among their peers, producing long recommendation "cascades."

In this report, Constant Pieters and Aurélie Lemmens examine this important aspect of customer referral value: To what extent do referred customers pass on the referral they received to others, and what drives this behavior?

Based on an analysis of large-scale survey data among U.S. movie viewers, they find that, on average, customers acquired via referrals do not have significantly different referral value than other customers.

First, exposure to WOM referrals is non-random; customers who were exposed to WOM referrals are systematically different than customers who were not. Ignoring this self-selection mechanism leads to an overestimation of the effect of referral exposure on referral value.

Second, a moderated mediation analysis shows that the mediation of satisfaction explains almost 80% of the total effect of WOM referral exposure on referral value. Referred customers who receive referrals that do not fit their tastes well (badly matched referrals) end up less satisfied than non-referred customers, leading them to refer less in turn.

The results suggest that managers should use WOM acquisition strategies cautiously as they may be not as successful in attracting customers with a high referral value as they are in recruiting profitable customers. Moreover, managers should not expect long chains or cascades of referrals as a result of WOM acquisition strategies.

Finally, companies should make sure their prospective customers have realistic expectations prior to consumption (for example, by means of information tools), and should encourage referrers to take the recipient's tastes into account when referring (for example, by means of matching tools).

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Introduction

Companies show a growing interest in managing the many word-of-mouth (WOM) interactions between their customers, for instance the product recommendations—further denoted *WOM referrals* (Brown and Reingen 1987; Trusov et al. 2009)—customers make to others. Many firms encourage such WOM referrals with or without monetary incentives, for example by means of WOM seeding strategies (Godes and Mayzlin 2009; Haenlein and Libai 2013; Hinz et al. 2011). Examples of such seeded WOM are the ones offered by the marketing company *BzzAgent*. The company generates WOM communication for its company clients by encouraging a panel of consumer agents (*BzzAgents*) to share their opinion about the client's products. Customer referral programs or member-get-member campaigns are other popular examples of WOM acquisition strategies (Garnefeld et al. 2013; Schmitt et al. 2011; Verlegh et al. 2013). Firms, such as *Dropbox* or *Spotify*, reward existing customers for bringing in new customers, with additional free storage space or a free premium account. WOM is not only seen as relatively cheap compared to other acquisition tools (e.g., advertising campaigns), it is also perceived as a more persuasive, credible, and a better targeted source of information (Bone 1995; Duhan et al. 1997; Murray 1991).

Many academic studies have explored the impact of WOM in fostering new product adoption and diffusion (Aral and Walker 2014; Nair et al. 2010), or sales (Chevalier and Mayzlin 2006; Godes and Mayzlin 2009). Another stream of research has shown the ability of WOM in recruiting customers with higher margins and lower churn than customers acquired through other channels (Schmitt et al. 2011; Villanueva et al. 2008). Firms have experienced these benefits in practice as well. For instance, the *Dropbox* refer-a-friend feature increased signups from 100k to four million users in 15 months.[1]

Nevertheless, an important question remains whether the customers recruited by referral also turn out to be good advocates of the firm. In other words, do they pass on the referral they received to others? This question was raised by Villanueva et al. (2008) who explain that customers should not only contribute to customer equity of the firm by the stream of their future cash flows, but also by generating WOM referrals. Likewise, Kumar et al. (2010) recently pointed out the importance of recruiting customers not only based on their customer lifetime

[1] http://www.referralcandy.com/blog/referrals-built-dropbox-empire/

value (CLV), but also taking into account their customer referral value (CRV), that characterizes the number of WOM referrals a customer makes. They find that the customers with the highest CRV are typically not the ones with the highest CLV. The success of WOM referral strategies does not only depend on the CLV of the acquired customers to the firm but also on the extent to which referred customers continue spreading the good word among their peers (Haenlein and Libai 2013), which would allow the production of long recommendation cascades or referral chains (Goel et al. 2012; Leskovec et al. 2007).

Several studies have recently investigated the effect of WOM referral exposure on WOM referral giving. These are summarized in Table 1 (Tables follow References throughout).[2] One stream of research has found, using individual-level survey data, a positive correlation between receiving and giving referrals (File et al. 1994; Sheth 1971; Uncles et al. 2013; Von Wangenheim and Bayón 2006). Recently, Yang et al. (2012) also found a synergy effect between receiving and giving referrals in that customers get utility from engaging in both actions. These results have been corroborated by a second stream of studies that has analyzed aggregate time-series of customer acquisition via referrals (Trusov et al. 2009; Villanueva et al. 2008). They concluded that customers exposed to WOM referrals contribute to higher referral acquisition rates in future time periods, compared to customers acquired through traditional marketing channels. A third stream of work has collected individual-level real-life referral network data (Goel et al. 2012; Leskovec et al. 2007). In contrast to what other studies would have predicted, they find that cascades of referrals are rare in practice, suggesting that the effect of referrals on subsequent referral value might actually be more limited than previously assumed.

This paper readdresses the question of the effect of receiving a referral on a customer's referral value. Figure 1 (Figures follow References throughout) illustrates our research question graphically. Circles represent acquired customers and arrows represent customer-to-customer WOM referrals. Our paper investigates whether the fact that an arrow is pointing at a given customer (e.g., customer 4, the grey circle) has an influence on the number of arrows originating from this customer and pointing at others. In case of a large effect, long recommendation cascades or referral chains should be observed.

[2] For conciseness, we exclude from the table the studies that have solely focused on outcomes different than WOM referral giving (e.g., adoption, diffusion, sales or CLV).

In contrast to previous work, this study takes into account the potential self-selection mechanism by which receiving a product recommendation is a non-random process. Previous work points out to the possibility that the customers exposed to referrals are intrinsically different from the customers non-exposed to referrals. For instance, Uncles et al. (2013) note that customers with a wide circle of friends and a greater interest in products naturally receive and make more referrals than others. We expect two sources of endogenous selection. First, some customers may be more likely to activate others to discuss their consumption experiences, while simultaneously being more inclined to seek social contacts. Similarly, some products are simply more likely to be talked about (Berger and Schwartz 2011), leading to a potentially spurious correlation between receiving and giving referrals. From a managerial viewpoint, it is important to correct for endogeneity because one could erroneously attribute the differences in referral value to the exposure to referrals, and thus overestimate the effectiveness of WOM acquisition strategies. To solve this problem, we use an instrumental variable approach in which we specify a selection equation and allow the error terms of the various equations to be correlated (Skrondal and Rabe-Hesketh 2004).

In addition to measuring the effect of referral exposure to a customer's subsequent referral value, the paper also contributes to the literature by shedding light on the mechanisms driving this effect. Understanding the underlying mechanisms provides guidelines on how to improve WOM strategies. To do so, we perform a moderated mediation analysis. First, the model tests the moderating role of referral match, the extent to which referrals are well-matched to the recipient's preferences. Second, we investigate the mediating role of customer satisfaction.

We collect individual referral data via a large-scale survey among a sample of 851 customers in the motion-picture industry. The experiential and intangible nature of movie consumption makes WOM referral information important in this industry (Murray 1991; Neelamegham and Jain 1999). Our data indicate the presence of a strong endogenous selection mechanism through which the customers who received a movie recommendation turn out to be intrinsically different from the customers who did not. After controlling for endogeneity, we find that, on average, exposure to WOM referrals has no effect on a customer's referral value. Interestingly, the results—when ignoring endogeneity—erroneously point to a positive relation between receiving and giving referrals. The moderated mediation analysis shows that, when referrals are ill-matched with the recipient's preferences, the referred customers end up less satisfied with the referred movie than non-referred customers, leading to a lower referral value. We find that this mechanism accounts for the majority (almost 80%) of the total effect. We conclude the paper by providing a number of suggestions for firms to improve the satisfaction of referred customers and, by this, the success of their WOM referral programs.

The remainder of this paper is structured as follows. In the next section, we provide a theoretical background to shed light on the relationship between receiving and giving WOM referrals. We then present the data, the methodology and the empirical application. This paper closes with a discussion of managerial implications and directions for future research.

Theoretical Framework and Hypotheses

An overview of our theoretical framework is given in Figure 2. We suggest that exposure to WOM referrals can influence the referral value of customers through the mediating effect of satisfaction. The positive effect of satisfaction on WOM referral intention and behavior is relatively well-established (Anderson 1998; De Matos and Rossi 2008). Hence, we verify this relationship in our empirical analysis. However, a prerequisite for establishing the mediating role of satisfaction is to show that WOM referral exposure affects satisfaction. The effects of WOM exposure on satisfaction are less known. Below, we provide a theoretical background to these effects.

Impact of WOM referral exposure on satisfaction

We define satisfaction as the pleasurable fulfillment of service (Shankar et al. 2003), and use the expectancy disconfirmation model to develop our arguments (Oliver 1980). The expectancy disconfirmation model is a comparative model of customer satisfaction that predicts satisfaction to be the difference between expectations and perceived performance. A customer is predicted to be satisfied if perceived performance exceeds her expectations, whereas a customer is dissatisfied when perceived performance falls short of expectations (Oliver 1980). A referral a customer receives acts as information prior to purchase upon which the customer can base her expectations regarding performance quality (Anderson and Salisbury 2003; Murray 1991; Zeithaml et al. 1993). In the motion-picture industry, the role of WOM in forming such expectations is known to be particularly important because of the experiential and intangible nature of movie consumption (Murray 1991; Neelamegham and Jain 1999), which makes it hard for customers to form expectations by other means. Below, we provide several arguments for a positive effect of WOM referral exposure on expectations, and thus indirectly a negative effect on satisfaction, consistent with the expectancy disconfirmation framework (Oliver, 1980; Westbrook, 1987; Zeithaml et al., 1993).

First, the product or service referrals received by customers are positive in nature and made by customers who positively evaluated the product or service. The more someone enjoyed a movie, the higher his likelihood to share his positive experience and refer it to friends (Anderson 1998). Through this mechanism, referred customers are likely to receive above-than-average positive information about a movie, compared to non-referred customers, and so to form high expectations about the referred movie.

Second, referrals are known to be a particularly valuable source of information for customers. According to the accessibility/diagnosticity theory (Feldman and Lynch 1988), information in memory is likely to influence the consumer when it is accessible and diagnostic (Bone 1995; Feldman and Lynch 1988; Herr et al. 1991). Referrals are accessible in that they are easy to retrieve, mostly because of their vividness (Herr et al. 1991). Referrals also have a high diagnostic value because, unlike advertising, they are transmitted by a non-commercial source, and therefore are generally seen as credible and trustworthy (Bone 1995).

Third, research on consumer herd behavior and informational cascades suggests that customers exposed to WOM referrals tend to disregard their own information and follow the choices made by others (Bikhchandani et al. 1998). This behavior leads to suboptimal outcomes (Banerjee, 1992). Customers believe that other customers have informational advantages about the product (Huang and Chen 2006), and may even use simple heuristics to drive their decision such as “if everyone tells me to watch this movie, I should go see it, because it should be a great movie.” Therefore, customers infer product quality prior to purchase, and hence form expectations, from others’ choices and evaluations.

As argued above, we expect that through these mechanisms, referred customers are more likely to have higher expectations, end up being disappointed, and are less satisfied with their movie experience than non-referred customers. Formally, we predict:

H1: Customers exposed to WOM referrals are, on average, less satisfied with their product or service consumption experience than customers not exposed to WOM referrals.

Moderating role of the match of the referrals with the recipient's preferences

While we expect a negative main effect of WOM referrals on satisfaction, it is possible that some of the customers who are exposed to WOM referrals turn out to be more satisfied with their product choice than others. One important factor that can moderate the relationship between the exposure to WOM referrals and satisfaction is the degree to which a referral's recipient receives referrals that are well-matched to his or her preferences.

In contrast to companies and other untargeted sources of information, the referring customer tends to have a good knowledge about the referred customer's tastes, making his or her referrals well-matched with the recipient's preferences (Dichter 1966). As Duhan et al. (1997) argue, influential recommendations require knowledge of both the product and the person receiving the recommendation, especially for products with affective evaluative cues (subjective criteria such as taste), such as movies. Strong ties, for example close friends, are likely to be knowledgeable of each other's tastes and the relevance of their information (Brown and Reingen 1987; Duhan et al. 1997). Moreover, homophily, the tendency for people to interact with people like them, suggests that customers are likely to share their experience with people that are similar to themselves (Brown and Reingen 1987; McPherson et al. 2001; Schmitt et al. 2011; Van den Bulte and Wuyts 2007). The homophily in taste between these customers is likely to increase the odds of satisfaction on the recipient side.

We expect that the extent to which customers receive well-matched referrals will moderate the negative effect of exposure to WOM referrals on satisfaction. In particular, referred customers who typically receive well-matched referrals are expected to show a higher level of satisfaction than customers who typically receive ill-matched referrals. Formally:

H2: The degree to which a referral's recipient receives well-matched referrals moderates the relationship between the exposure to WOM referrals and satisfaction, in that customers who are exposed to referrals and receive well-matched referrals are more satisfied with the product or service consumption experience than customers who receive ill-matched referrals.

Impact of satisfaction on WOM referral value

A second condition for satisfaction to be mediating the effect of WOM referral exposure and the referral match moderator on WOM referral value is that there also exists an effect of satisfaction on WOM referral value. Customer satisfaction with a consumption experience is regarded as a key antecedent of product- or service-related WOM (Anderson 1998; De Matos and Rossi 2008; Westbrook 1987). The higher the satisfaction of an individual with a consumption experience, the greater the amount of recommendations she is likely to make. Several reasons for this effect are captured in the utility-based model proposed by Anderson (1998), who asserts that a customer's utility of referring a product of service increases as the satisfaction with product experience increases.

First, extreme information is more accessible than moderate information (Anderson 1998). A very satisfying product experience is more memorable and thus more likely to be talked about than a less satisfying product experience. Moreover, extreme information has been found to be more diagnostic: an extreme cue provides more utility in discriminating between alternative categories than a less extreme cue (Anderson 1998; Skowronski and Carlston 1989; Skowronski and Carlston 1987). As such, higher satisfaction has a strong impact on WOM behavior as it allows customers to easily categorize the product in the "talk about" compared to "not talk about" category while moderate satisfaction makes categorization ambiguous.

Second, customers often engage in WOM referrals to bring back positive feelings to relive the pleasurable product experience and elicit positive feelings (Berger 2014). Dichter (1966) refers to WOM referrals as having the function of "verbal consumption." A more satisfying consumption experience is therefore more likely to be talked about for these purposes as it is surrounded by more positive feelings that can be retrieved.

Third, a common motive for customers to engage in WOM referrals is self-enhancement (Berger 2014; De Angelis et al. 2012), where customers talk about favorable and interesting things to look good in front of their peers and create good impressions. Customers can get positive recognition from others by linking these favorable impressions with themselves by talking about them. For this purpose, the more positive a consumption experience is perceived by the customer, the more it makes the customer look interesting in front of their peers, making it more suitable to talk about for self-enhancement purposes.

All in all, these motives suggest that the more satisfied a customer is, the more likely she will share her experience with others. A recent meta-analysis by De Matos and Rossi (2008) gives strong empirical support for this positive relationship. While we do not formally hypothesize the relationship between satisfaction and referral value, we aim to empirically verify the findings above with a moderated mediation analysis.

Data and Variables

In order to test our hypotheses, we ran a large-scale survey in August 2014 among movie viewers in the United States. The survey investigated the WOM referral behavior of the respondents and contained a number of psychometric scales necessary to test our hypotheses. In order to control for inherent differences that exist between the movies watched by the respondents, we combined the survey with data on movie characteristics that we extract from the *Internet Movie Database* (*IMDb*; www.IMDb.com).

Our choice to use a survey is consistent with current practice in the WOM literature (Anderson 1998; File et al. 1994; Neelamegham and Jain 1999; Uncles et al. 2013; Von Wangenheim and Bayón 2006; Westbrook 1987; Yang et al. 2012). In light of our research objectives, our survey items have multiple benefits over other data types such as social network data (Goel et al. 2012; Leskovec et al. 2007), or aggregate time-series (Trusov et al. 2009; Villanueva et al. 2008). First, they allow us to measure individual psychometric constructs (e.g., satisfaction with a consumption experience) that are latent and difficult to measure with secondary data. Second, they provide us the instruments we need to handle the issue of endogenous selection. As the selection mechanism operates on the individual level—customers who are exposed to WOM referrals are systematically different from those who were not—it is challenging for aggregate time-series data to capture individual-level selection effects. Large-scale social network data, albeit on the individual level, suffers from similar concerns as finding instrumental variables is extremely challenging, although (costly) field experiments or (difficult to find) natural experiments may be employed (Aral and Walker 2014). As survey data is prone to measurement error and recollection bias, which may limit the generalizability of the study, we use a structural equation model with a measurement component in order to account for measurement error (Bagozzi and Yi 2012; Kline 2011). We also check that our results do not suffer from a potential recollection bias in the "Robustness Checks" section.

Measures and variable operationalization

Participants were recruited using the *Amazon Mechanical Turk* (*MTurk*) service.[3] Workers were allowed to participate if they had seen a movie in a movie theater in the past 12 months.[4] In order to receive $.5 payment after completing the survey, respondents received a randomized code to enter in the *MTurk* environment. The survey consisted of two parts. First, participants were asked to recall their last movie visit (for a recent paper using a similar survey see Yang et al. 2012). In this part of the survey, participants reported the title of the last movie they saw at a movie theater, and were asked to answer a set of questions with this movie in mind (see Table 2 for an overview of the items and scales):

- *WOM referral exposure*. Respondents answered for the movie they indicated as the last movie they had seen, whether they were exposed to WOM referrals prior to seeing the movie. This binary variable takes value one for respondents who reported being exposed to WOM referrals and zero for those who were not.
- *Satisfaction.* The degree of satisfaction of the respondent with his/her movie of choice was measured with three items (one reversed) and seven-point Likert scales, adopted from Maxham III and Netemeyer (2002).
- *WOM referral value.* We capture WOM referral value by measuring the total number of referrals a customer has made and plans to make in the future. To account for the long-tailed distribution, we take the natural logarithm of the total of number of prospective customers a consumer referred to and intends to refer in the future, plus one to account for zero values.

In the second part of the survey, participants were asked to complete items that were not specific to the movie in question:

- *Referral match.* We measure the degree to which a customer receives referrals that are well-matched to his or her preferences using three items and seven-point scales. Participants were asked how they would qualify the movie recommendations they receive in general, how satisfied they are with the movie recommendations they receive in general, and how well the individuals who generally recommend them movies know the participant's movie tastes.

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[3] For a recent empirical application of *MTurk* in marketing see for example Lamberton and Rose (2012). For discussions on the *MTurk* platform and expected reliability of the data see Buhrmester et al. (2011) and Peer et al. (2014).

[4] Following recommendations by Peer et al. (2014), U.S. workers with at least a 95% acceptance rate and at least 500 accepted tasks were sampled. Moreover, we applied the procedure outlined by Peer et al. (2012) to prevent sampling multiple responses per worker ID.

These items capture the extent to which, *in general*, the referrals a participant receives match her preferences. Because we consider this construct as a moderator, rather than a mediator, we measure referral matching using a construct not specific to the focal movie consumption episode, but as an individual-level trait that is determined independently of the current consumption episode.

We also collected additional individual-level variables that serve as control variables and instrumental variables in the model (see "The Model" section for how all variables enter the model):

- *Opinion seeking*. The scale was adopted from Flynn et al. (1996) and captures the extent to which a customer looks for opinions from others before choosing movies with six seven-point Likert items (three reversed).
- *Opinion leadership.* The scale was adopted from Flynn et al. (1996) and captures the extent to which the customer exerts influence on the movie choices of others with six seven-point Likert items (three reversed).
- *Gender* and *age.* Participants were also asked about their gender (male coded as 1, female as 0) and age (continuous scale).

Finally, we also collected movie-level data on the movies from *IMDb*:

- *Movie rating*. We control for quality differences between movies using the movie ratings provided by *IMDb* users.
- *Opening weekend box-office revenues.* This variable measures the movie revenues up to the opening weekend and hence captures the popularity of the movie early in its lifecycle. We use the natural logarithm of this variable to account for its long-tailed distribution.

Sample and descriptive statistics

We collected data from 900 respondents. We excluded respondents who claimed to have seen the movie before the release date shown on *IMDb* and respondents who reported a movie which actual release date, according to *IMDb*, was before 2012 (because of the short lifecycle of movies, it is unlikely that these customers saw the movie in the theater). We also removed duplicate IP addresses, respondents for which we could not match the self-reported movie title with the *IMDb* repository, as well as movies for which there was missing data.

Our final sample consists of 851 respondents. Among the respondents, 320 (about 38%) mentioned having been exposed to WOM referrals prior to seeing the movie, the remaining 531 (about 62%) were not exposed to WOM referrals. Table 3 shows descriptive statistics. In line with previous research, customers who indicated to be exposed to WOM referrals seem to make more referrals, compared to customers who were not exposed to WOM referrals ($T_{(849)} = -6.824$, $p < .001$) when we do not control for any other variables. Moreover, when we do not control for endogeneity, customers who were exposed to WOM referrals seem to show a higher satisfaction and referral value than those who were not exposed to WOM referrals (e.g., satisfaction 1: $T_{(849)} = -5.062$, $p < .001$). Another interesting difference is that customers who were exposed to WOM referrals have a higher tendency to be opinion seekers (e.g., opinion seeking 1: $T_{(849)} = -6.905$, $p < .001$). Customers exposed to WOM are also slightly younger ($T_{(849)} = 2.680$, $p = .008$), but both groups do not differ in the proportion of men/women ($T_{(849)} = -.057$, $p = .954$). In terms of their movie choice, customers exposed to WOM tend to choose better rated movies ($T_{(849)} = -9.414$, $p < .001$) and movies with higher opening weekend box-office revenues ($T_{(849)} = -4.127$, $p < .001$).

Measurement properties

We first performed a confirmatory factor analysis measurement model to validate and purify the multi-item scales (Anderson and Gerbing 1988). The items of the latent constructs satisfaction, referral match, opinion seeking and leadership scales load on separate factors with free covariances between factors. No cross-loadings were allowed. For each latent variable, we specify for respondent i, and indicator j:

$$y_{ij} = \nu_j + \lambda_j \eta_i + \varepsilon_{ij}, \tag{1}$$

where η_i is the latent variable, y_{ij} is the observed indicator, ν_j is an intercept, λ_j is a loading, and error term $\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon_{ij}})$. We fixed one loading of each factor to one for identification purposes, and allow for within-factor covariances between errors of negatively (reversed) scaled items to parsimoniously control for response styles of negatively worded items (DiStefano and Motl 2006; Marsh 1996; Tomás and Oliver 1999). After dropping the first opinion leadership item with a poor standardized loading (.41; see Table 2), the measurement model showed adequate fit ($\chi^2 = 406.671$; Comparative Fit Index (CFI) = .962; Tucker-Lewis Index (TLI) = .953; Root Mean Squared Error of Approximation (RMSEA) = .057; Standardized Root Mean Square Residual (SRMR) = .045).

Table 4 shows the Average Variance Extracted (AVE), Composite Reliability (CR) and the correlations between the latent variables (Bagozzi and Yi 2012; Fornell and Larcker 1981). The results show that the factors are reliable, as shown by high CRs. We assess discriminant validity by means of the three Fornell and Larcker (1981) criteria. First, the correlations between latent variables are clearly less than one. Second, the AVEs of all latent variables exceed 50%. Third, the AVEs of all latent variables exceed the variance shared with other latent variables (squared correlations). Using the same criterion, we also check discriminant validity between the factors and the single indicator variables and find that satisfaction and WOM referral value ($\rho^2 = .284$), and opinion leadership and WOM referral value ($\rho^2 = .125$) are discriminant valid given that the respective AVEs are larger than the squared correlations. Overall, we conclude that we have reliable and discriminant valid measures.

The Model

We use a structural equation model (SEM) to investigate the drivers of WOM referrals, augmented with the measurement model in Equation 1. SEM appropriately deals with survey data accounting for measurement error (Bagozzi and Yi 2012; Kline 2011) and allows us to perform the moderated mediation analysis (Figure 2) while accounting for the endogenous selection mechanism. Below, we describe our model and explain how we account and test for endogeneity.

Model specification

We specify the following structural equations:

$$\mathrm{WOMreferralexposure_i} = \alpha_o + \alpha_1 \mathrm{Opinionseeking_i} + \alpha_2 \ln(\mathrm{Openingweekendboxofficerevenue_i}) + \alpha_3 \mathrm{Movierating_i} + \alpha_4 \mathrm{Gender_i} + \alpha_5 \mathrm{Age_i} + \varepsilon_{1,i} \quad (2)$$

$$\mathrm{Satisfaction_i} = \beta_1 \mathrm{WOMreferralexposure_i} + \beta_2 \mathrm{Referralmatch_i} + \beta_3 \mathrm{WOMreferralexposure_i} * \mathrm{Referralmatch_i} + \beta_4 \mathrm{Movierating_i} + \beta_5 \mathrm{Gender_i} + \beta_6 \mathrm{Age_i} + \varepsilon_{2,i} \quad (3)$$

$$\mathrm{WOMreferralvalue_i} = \gamma_0 + \gamma_1 \mathrm{WOMreferralexposure_i} + \gamma_2 \mathrm{Satisfaction_i} + \gamma_3 \mathrm{Opinionleadership_i} + \gamma_4 \mathrm{Movierating_i} + \gamma_5 \mathrm{Gender_i} + \gamma_6 \mathrm{Age_i} + \varepsilon_{3,i} \quad (4)$$

with the errors $\varepsilon_{1,i}, \varepsilon_{2,i}, \varepsilon_{3,i} \sim N(0, 0, 0; \Sigma)$. The specification of the error covariance matrix is defined in the next subsection. Consistent with the mediation literature, we specify a direct effect of WOM referral exposure on WOM referral value (Preacher et al. 2007; Zhao et al. 2010). Equation 2 is specified as a linear probability model (Olsen 1982). The intercept in the satisfaction equation is suppressed for identification purposes. We estimate the measurement model and structural model simultaneously in *Mplus* (Muthén and Muthén 1998-2012) using full-information robust (to deviations from normality) maximum likelihood.[5] We follow the procedure by Klein and Moosbrugger (2000) to estimate the latent interaction effect in Equation 3.

Accounting for endogenous selection

A key feature of our approach is that we consider the endogenous process by which customers select themselves into being exposed to WOM referrals. Specifically, we argue that the effects of WOM referral exposure are likely to be driven by endogenous selection on unobservables. Two types of endogeneity are likely to occur.

First, some customers may be more likely to activate others to discuss their consumption experiences, while simultaneously being more inclined to seek social contacts. For example, some customers may simply be more social in that they often talk with other customers about their favorable movie experiences, but are also exposed to movie-related conversations from their peers. Moreover, some customers may simply be more involved with the product category. They like to talk about movies with others and do not hesitate to ask for interpersonal advice when they need information about a movie. Second, some products are simply more likely to be talked about (Berger and Schwartz 2011) leading to a potentially spurious correlation between WOM input and output. For example, some movies are more provocative than others, such that they generate a lot of chatter.

To correct for endogeneity, we use an instrumental variable procedure and specify a WOM referral exposure equation (Equation 2) as a function of a number of instruments, and free off-diagonal elements of the Σ covariance matrix of the structural error terms (Skrondal and Rabe-Hesketh 2004). We use two instruments, opinion seeking to account for the potential selection at

[5] Given that we use robust maximum likelihood to estimate the model, we rescale the test statistic using the scaling correction factor described by Satorra (2000) when performing nested model (likelihood ratio) comparison tests.

the customer level, and opening weekend box-office revenue (in natural logarithm) to account for the potential selection at the movie level. We demonstrate the statistical properties of these instruments in the next section. Our choice for these instruments is justified by the fact that we expect opinion seekers to show a high tendency to seek information from their peers when buying a new product or service, and hence to be exposed to WOM referrals (Flynn et al. 1996). Moreover, we expect that the better a movie performs during the first weekend, the more buzz it will generate and the larger the base of adopters who will recommend the movie to others after the first weekend.

Testing the instruments

We use a three-pronged approach to empirically test for the strength and validity of our instruments. For the strength, Stock et al. (2002) provide a rule of thumb in that the F-statistic on the excluded instruments in the first stage should be greater than ten. A joint test of the R^2 increase (from .099 to .143) of the excluded instruments yields $F_{(2, 845)} = 21.69$, while both instruments significantly explain WOM referral exposure ($p = .043$ and $p = .001$), indicating that the instruments are empirically strong.

For the validity, we test for overidentifying restrictions (Kenny and Milan 2012). For each equation, we sequentially free paths from one of the instruments to the dependent variables (satisfaction and WOM referral value) in the model. The additional paths were not significant (highest Z = -.696, $p = .487$), and adding them did not significantly increase model fit (highest $\chi^2 = .473$, $p = .492$), indicating that the instruments are empirically valid.

Finally, we also tested for endogeneity using the Durbin-Wu-Hausman (DWH) test. We find that the residual is significant in the satisfaction equation (Z = 8.671, $p = .003$) whereas it is not significant in the WOM referral value equation (Z = 1.408, $p = .235$). We conclude that the instruments are strong and valid and that WOM referral exposure is endogenous in the satisfaction equation (see Dinner et al. 2014, for a similar procedure).

Moderated mediation analysis

As shown in Figure 2, the expected impact of WOM referral exposure on referral value is not only mediated by satisfaction, but its effect on the satisfaction mediator is also expected to be moderated by referral match. As such, we expect a moderated mediation (Preacher et al. 2007). Consistent with the mediation literature and our model, we decompose the total effect of exposure to WOM referrals on post-consumption WOM value in a conditional indirect (mediation) effect and a direct effect (Preacher et al. 2007; Zhao et al. 2010). We specify the indirect effect, which is conditional on a value of the referral match moderator, as:

$$\text{Indirect effect} = \gamma_2(\beta_1 + \beta_3 * \text{Referralmatch}), \tag{5}$$

while the direct effect is simply γ_1. The total effect is the sum of both effects:

$$\text{Total effect} = \gamma_1 + \gamma_2(\beta_1 + \beta_3 * \text{Referralmatch}). \tag{6}$$

The total effect informs us whether customers exposed to WOM referrals differ in their referral value from the customers not exposed to WOM referrals. The indirect effect allows to test whether satisfaction mediates the relationship between WOM referral exposure (and the referral match moderator) and referral value. Because the indirect effect is conditional on the value of the moderator, we report these effect for three values of the moderating referral match: a low value equal to the mean minus two standard deviations, the mean value, and a high value equal to the mean plus two standard deviations. We report the 95% bootstrapped (10,000 iterations) confidence intervals (CI) around these effects (Preacher et al. 2007; Zhao et al. 2010). We also compute the proportion mediated (Alwin and Hauser 1975; MacKinnon et al. 2007), which is given by:

$$\text{Proportion mediated} = \frac{|\text{Indirect effect}|}{|\text{Indirect effect}| + |\text{ Direct effect}|}. \tag{7}$$

Results

We estimate different variants of our model: (i) Model 1 that does not account for endogenous selection, nor mediation (Equation 4 only), (ii) Model 2 that specifies all three equations, but does not control for endogeneity (i.e., the errors are not correlated), (iii) Model 3, our full model accounting for endogeneity (i.e., the errors are now correlated) and mediation. Parameter estimates of these models are reported in Table 5. Below, we first investigate whether exposure to WOM referrals influence the referral value of customers. We then show that not accounting for endogeneity would have substantially changed the answer to this question. Finally, we explore the mechanism linking exposure to WOM referrals and a customer referral value by testing each of the hypotheses.

Does exposure to WOM referrals influence customers' referral value?

Table 6 depicts the estimated total effect of WOM referral exposure on a customer referral value according to Model 3 and decomposes it into a direct and an indirect effect. A graphical representation of this total effect decomposition is provided in Figure 3. The total effects (darkest bars) show that customers who received a movie referral do not have a higher probability to refer the movie to others than customers who did not receive a referral. In fact, for mean and high values of the referral match moderator, the total effect of WOM referrals on WOM referral value, taking into account all paths, is negative yet indistinguishable from zero (95% bootstrap CI (-.701; .073) for mean referral match and (-.586; .263) for high referral match both contain zero). However, for a low value of the moderating variable referral match, the total effect becomes significantly negative (95% bootstrap CI (-.877; -.051) does not contain zero). These results provide us a first important managerial insight: *customers exposed to WOM referrals do not have a higher referral value than the customers not exposed to WOM*. At best, they refer the movie they have seen to as many other customers as the customers not exposed to WOM referrals. In some cases, they tend to refer it to less people than the customers who were not exposed to WOM referrals.

This total effect can be decomposed into a direct effect (mid-grey bars) and an indirect (mediating) effect via satisfaction (light grey bars). As shown in Figure 3, the effects are of opposite signs, what Zhao et al. (2010) name "competitive mediation", and also referred to as "inconsistent mediation" (MacKinnon et al. 2007). We find a negative indirect effect of WOM referral exposure on WOM referral value, mediated by satisfaction. The indirect effect is significant for low and mean values of referral match (95% bootstrap CIs resp. (-1.013; -.224) and (-.850; -.105) do not contain zero). For high values of referral match, we find an indirect effect indistinguishable from zero (95% bootstrap CI (-.727; .093) contains zero). Contrasting with this negative indirect effect, we find a significant direct effect (95% bootstrap CI (.022; .294) does not contain zero) of WOM referral exposure on WOM referral value. While satisfaction partially mediates the relationship between WOM referral exposure and a customer referral value, the proportion mediated for low, mean, and high values of referral match is respectively .789, .736, and .648, suggesting that a majority of the total effect of WOM referral exposure on WOM referral value comes from the indirect effect. Following Kenny (2014), this is close to a full mediation as the share approaches 80%. These results provide us a second important managerial insight: *satisfaction plays a major role in the extent to which customers who receive a movie referral would pass it on to others and therefore be of high referral value.*

Finally, Figure 3 offers an interesting contrast between customers who typically receives ill-matched referrals (left panel of Figure 3, "low referral match"), and customers who usually receives well-matched referrals (right panel of Figure 3, "high referral match"). The indirect effect of exposure to WOM referrals via satisfaction is less pronounced for the second segment of customers compared to the first segment of customers. In particular, the first segment ends up recommending the movie less to others when they go for a movie they have been recommended to than when the movie was not recommended to them. For the second segment, there is no difference in the number of referrals they make whether the movie has been referred to them or not. The results provide us a third important managerial insight: *the satisfaction of referred customers who receive well-matched movie referrals is not sufficiently high to make their referral values higher than the referral value of customers who do not receive any referral.*

How do the results change when not accounting for endogeneity?

To highlight the role of endogeneity, we contrast these results with the results from Model 1, which does not control for it. In Table 5, we find a positive and significant effect of WOM referral exposure on WOM referral value ($\gamma_1 = .256$, $p = .001$, 95% bootstrap CI (.109; .404) does not contain zero). This result is consistent with previous research and indicates that the apparent positive correlation between receiving and giving WOM referrals is due to endogenous self-selection rather than the exposure to WOM itself.[6]

What explains the effect of exposure to WOM referrals on customers' referral value?

Our model also provides insights into the mechanisms that relate exposure to WOM referrals and WOM referral value, which allow us to test the hypotheses (see Table 5, Model 3). Based on the moderated mediation analyses we find, consistent with H1 and H2, that the effect of WOM referral exposure on referral value is moderated by the referral match and mediated by satisfaction. We find a negative and significant main effect of WOM referral exposure on satisfaction ($\beta_1 = -.957$, $p = .013$). We explain this negative effect by the fact that customers who

[6] Note that the change in the size of the standard errors (efficiency loss) between Model 1 and Model 3 (approximately a factor two) is in line with previous research (Kornish and Ulrich 2014; Zhang et al. 2009), which we consider reasonable.

received a movie referral tend to form higher expectations about the movie they are about to see, increasing the odds that they will end up disappointed and hence less satisfied compared to customers who did not received a referral. This effect is positively moderated by the referral match ($\beta_3 = .233$, $p = .057$), consistent with H2. Customers who tend to receive referrals that fit their preferences end up more satisfied with the movie than those who receive ill-matched referrals. When the referring customer has a good knowledge about the movie preferences of the referred customer, for example in case of strong ties, we find that the negative effect of receiving a referral becomes smaller in intensity. As shown in Figure 3, the indirect effect becomes insignificant for high values of referral match.

To complete the mediating effect of satisfaction, the results also show a positive and significant effect of satisfaction on WOM referral value ($\gamma_2 = .455$, $p < .001$). Customers who are more satisfied get more utility from engaging in WOM referrals themselves and spread the word to a larger audience (Anderson 1998; De Matos and Rossi 2008). Finally, we find a small but significant positive direct effect of WOM referral exposure on customer referral value ($\gamma_1 = .156$, $p = .024$) as we described in the prior subsection. Although the direct effect accounts for a small share of the total effect, it may capture several interesting mechanisms, which we do not identify in our study. For example, the theory of emotional contagion shows that emotions can flow from one person to another (Hennig-Thurau et al. 2006). Arousal that drives customers to engage in product-related conversations (Berger 2011) can be transferred to the referral recipient, leading her to refer in turn. Alternatively, customers may engage in indirect reciprocity after receiving a favorable referral in that they reciprocate the act of receiving a successful referral by referring to others in their network (Wasko and Faraj 2005). Future research could shed more light on the nature of this small but significant positive effect by introducing additional mediators or moderators (Zhao et al. 2010).

Robustness checks

We check the robustness of these results to various scenarios. First, to investigate potential recollection bias, we restrict the sample to customers who saw the movie less than three months ago, resulting in a sample size of 660 customers (77.6% of the full sample). We find the coefficients of interest and the substantive conclusions to be identical.

Second, the literature suggests that early adopters might differ from late adopters (Rogers 1983), and such differences can have an effect of their referral value. We control for the timing of adoption (viewing) of the movie and include a variable that captures how many months after the movie release a respondent saw the movie to all three equations. We find that the additional parameters are insignificant in all equations (all $p > .344$), that the coefficients of interest remain substantively identical, and that the Bayesian Information Criterion (BIC) becomes larger (BIC = 45,785 with adoption timing compared to 45,766 without adoption timing).

Third, we checked the robustness of our results when allowing for a non-zero error covariance between Equations 2 and 4, in addition to the error covariance between Equations 2 and 3. We find that the quantities of interest are substantively identical and that the additional error covariance is virtually zero ($\sigma_{1,3} = -.008$, $p = .906$), and that the BIC becomes larger (BIC = 45,773).

Fourth, we account for the possibility that the direct effect of WOM referral exposure on WOM referral value may also be moderated by referral match. We add a main effect of referral match and its interaction with WOM referral exposure to Equation 4 and find that both paths are insignificant (resp. $p = .319$, $p = .202$), and that the model fit does not improve (BIC = 45,774).

Discussion

Our paper reveals a number of interesting findings about the relationship between receiving and giving WOM referrals. First, our results highlight the consequences of ignoring the endogenous selection process by which customers are exposed to WOM referrals. In contrast to previous research (Sheth 1971; Trusov et al. 2009; Uncles et al. 2013; Villanueva et al. 2008; Von Wangenheim and Bayón 2006), the results show that, on average, being exposed to WOM referrals does not affect the number of referrals a customer will make in turn.

Second, we get insights in the mechanisms that lead to these effects. The moderated mediation analysis reveals that referred customers who receive referrals that are poorly matched turn out to be less satisfied than non-referred customers, leading them to refer less in turn. This result supports the idea that not all referrals are equally useful. Effective recommendations should take the recipient into account and require knowledge of both the product and the person receiving the recommendation (Duhan et al. 1997). Consistent with a disconfirmation of expectations account (Oliver 1980), WOM referrals create unrealistic expectations about the movie a customer is about to view which are disconfirmed when seeing the movie, leading to lower satisfaction. The mediation of satisfaction accounts for the majority (for average customers: 73.6%) of the total effect of WOM referral exposure (moderated by referral match) on WOM referral value. These results contrast with previous research suggesting that customers acquired through WOM might be satisfied customers (Bolton et al. 2004; Uncles et al. 2013; Von Wangenheim and Bayón 2006).

Managerial implications

Our results offer a number of important managerial implications for firms interested in WOM acquisition strategies. First, while WOM acquisition strategies have certainly shown their potential in attracting higher CLV customers compared to other acquisition strategies (Schmitt et al. 2011; Villanueva et al. 2008), they are less likely to recruit customers with a higher referral value (Kumar et al. 2010). On average, we find that customers acquired via referrals do not have significantly different referral value than other customers. From a managerial viewpoint, it implies that firms can count on high revenues from customers recruited via referrals but should expect more limited cascades of referrals (i.e., the number of customers recruited) than what prior work has suggested (e.g., Trusov et al. 2009; Villanueva et al. 2008)

Second, our moderated mediation analysis pinpoints that companies should act with care when implementing WOM acquisition campaigns. It is critical not to encourage referrals between customers who know little about each other’s preferences. Incentivizing customers to increase the number of referrals they make, for example by offering them a monetary reward (Verlegh et al. 2013), might have a detrimental effect on the outcome as it might push customers to pay less attention to who they share their recommendation with. A solution can be to give customers incentives to share that are *conditional* on the adoption of the receiver and/or her future referral value (Garnefeld et al. 2013; Schmitt et al. 2011).

Third, the results suggest directions for firms on how to boost the length of referral cascades. One can be to offer technology and software solutions to their current customers that help them improving the satisfaction of the referred customers, and consequently their referral value. Different types of helping tools can be made available to them. For instance, *information tools* that provide a sensible description of the product and ensure realistic expectations about the referred products can be made available on a (online) customer platform. For physical products, free samples can be offered to share, while for services, informational videos can be provided to referring customers to show to their friends. In addition, firms could also offer *matching tools* that help the referring customers to better identify which of their friends would be potentially most satisfied with the referred product or service. For example, movie enthusiast websites (like *IMDb*), but also social networks such as *Facebook*, often allow users to specify their favorite movies or show the most recent ratings and reviews for each user when accessing their profile, effectively showing the movies they have seen and their ratings. Companies may even aid recommenders by using and analyzing historical data on customer preferences combined with demographic information, and come up with a list of friends that might also like the movie they have seen. In view of the increasing amount of data (sources) becoming available, matching tools undoubtedly have the potential to help customers to better target their recommendations.

Limitations and directions for future research

Our study suffers from several limitations that offer opportunities for future research. First, our study contributes to a growing stream of research that investigates the consequences of WOM referrals on future referrals (see Table 1). Similar to these papers, we focus on the consequences of positive WOM referrals. Studying the consequences of negative WOM was beyond the scope of the present research but can certainly reveal interesting new insights.

Second, we investigate the effect of WOM referrals on a customer referral value in general. It would be interesting to study the extent to which the content of these referrals also plays a role. Future research could distinguish between, for example very enthusiastic vs. mild endorsements, solicited referrals vs. unsolicited referrals (Fitzsimons and Lehmann 2004), or rewarded vs. not-rewarded referrals (Verlegh et al. 2013).

Third, like many studies on WOM referrals, we use self-reported data. A key reason for us to use survey data is that it allows us to study the process: the moderating and mediating mechanisms that jointly link receiving and giving referrals. While we control for potential measurement issues with a measurement model, the retrospective nature of the survey might limit the generalizability of our findings. Future research may augment similar survey data with secondary data on actual referral activity to further alleviate the potential recollection bias concerns and enhance the generalizability of the study.

Fourth, we reveal satisfaction to be a key factor in the process that leads to an effect of WOM referral exposure on WOM referral value. However, we do not capture complete evidence for the theoretical mechanisms we propose, which are based on expectations. Although the relationship between expectations and satisfaction is well-established (Oliver, 1980; Westbrook, 1987; Zeithaml et al., 1993), future research may be able to dig even further in the process, especially by showing an effect of WOM referral exposure on expectations, for example by means of lab experiments or multiple measures over time.

To conclude, we believe, in view of previous work and the current research, that WOM acquisition strategies can be potentially successful strategies for firms to consider but should be implemented with care if they want to benefit from long cascades of referrals.

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Tables

Table 1

Comparison of Current Research With Existing Research Studying the Effect of Receiving Referrals on Giving Referrals

Study	Industry	Type of data	Method	Level of aggregation	Control for endogenous selection	Model the underlying process	Key findings
Sheth (1971)	Razor blades	Interviews	Mean comparisons	Individual	No	No	25% of the respondents who were influenced by a personal source attempted to influence someone else compared to 9% of respondents who were not influenced by a personal source
File, Cermak, and Prince (1994)	Three B2B industries	Survey	OLS	Individual	No	No	Input WOM is positively associated with output WOM for two out of three industries
Von Wangenheim and Bayon (2006)	Energy providers	Survey	Mean comparisons	Individual	No	No	Referral switchers (customers who were acquired through positive WOM from other customers) are more likely to make a referral compared to other switchers
Leskovec, Adamic, and Huberman (2007)	Online retailing	Secondary data	Descriptive	Individual	No	No	Recommendations rarely successfully propagate
Villanueva, Yoo, and Hanssens (2008)	Web hosting	Survey and secondary data	VAR	Aggregate	No	No	Customers acquired through WOM generate more WOM compared to those acquired through traditional marketing channels
Trusov, Bucklin, and Pauwels (2009)	Online social networking	Secondary data	VAR	Aggregate	No	No	The long-term elasticity of new sign-ups with respect to WOM is approximately 20 times higher than for marketing events, and 30 times that of media appearances
Goel, Watts, and Goldstein (2012)	Various online services	Secondary data	Descriptive	Individual	No	No	Cascades of subsequent referrals are small
Yang et al. (2012)	Car industry	Survey	Joint utility model	Individual	No	No	There is a strong synergy effect between WOM generation and consumption
Uncles, East, and Lomax (2013)	Various B2C industries	Survey	Mean comparisons	Individual	No	No	Recommendation rates of customers who were referred are higher than customers acquired through other modes of acquisition
This study	Motion-picture industry	Survey and secondary data	SEM	Individual	Yes	Yes	On average, customers exposed to WOM referrals do not refer more or less than customers who were not exposed to WOM referrals; customers who receive badly matched referrals have a lower referral value

Table 2

Survey Items and Scales

Construct	Item	Scale
WOM referral exposure	Did anyone recommend you this movie before you saw it?	Yes / No
WOM referral value	How many people, approximately, did you recommend the movie to?	#
	How many people, approximately, do you intend to recommend the movie to in the future?	#
Satisfaction 1	I am satisfied with my overall experience with the movie	Strongly Disagree - Strongly Agree
Satisfaction 2	As a whole, I am not satisfied with the movie [b]	Strongly Disagree - Strongly Agree
Satisfaction 3	How satisfied are you overall with the quality of the movie?	Very Dissatisfied - Very Satisfied
Referral match 1	In general, how would you qualify the movie recommendations you receive?	Very Bad - Very Good
Referral match 2	In general, how satisfied are you with these movie recommendations?	Very Dissatisfied - Very Satisfied
Referral match 3	In general, how much do they know about your movie preferences? Their knowledge is …	Very Bad - Very Good
Opinion seeking 1	When I consider seeing a movie, I ask other people for advice	Strongly Disagree - Strongly Agree
Opinion seeking 2	I don't need to talk to others before I see a movie [b]	Strongly Disagree - Strongly Agree
Opinion seeking 3	I rarely ask other people what movies to see [b]	Strongly Disagree - Strongly Agree
Opinion seeking 4	I like to get others' opinions before I see a movie	Strongly Disagree - Strongly Agree
Opinion seeking 5	I feel more comfortable seeing a movie when I have gotten other people's opinions on it	Strongly Disagree - Strongly Agree
Opinion seeking 6	When choosing a movie, other people's opinions are not important to me [b]	Strongly Disagree - Strongly Agree
Opinion leadership 1	My opinion about movies seems not to count with other people [a b]	Strongly Disagree - Strongly Agree
Opinion leadership 2	When they choose a movie, other people do not turn to me for advice [b]	Strongly Disagree - Strongly Agree
Opinion leadership 3	Other people rarely come to me for advice about choosing movies [b]	Strongly Disagree - Strongly Agree
Opinion leadership 4	People that I know pick movies based on what I have told them	Strongly Disagree - Strongly Agree
Opinion leadership 5	I often persuade other people to see movies that I like	Strongly Disagree - Strongly Agree
Opinion leadership 6	I often influence people's opinions about popular movies	Strongly Disagree - Strongly Agree
Gender	What is your gender?	Male / Female
Age	What is your age?	#

[a] denotes an item dropped in the final measurement model; [b] denotes a negatively worded (reversed) item. Note: All "Strongly Disagree - Strongly Agree", "Very Bad - Very Good", and "Very Dissatisfied - Very Satisfied" scales are seven-point.

Table 3

Descriptive Statistics

	Complete sample (n = 851)		Customers exposed to WOM referrals (n = 320)		Customers not exposed to WOM referrals (n = 531)	
Variable	**M**	**SD**	**M**	**SD**	**M**	**SD**
ln(WOM referral value)	1.378	1.086	1.696	1.048	1.185	1.064
Satisfaction 1	5.850	1.207	6.116	.984	5.689	1.299
Satisfaction 2	5.378	1.875	5.538	1.913	5.282	1.847
Satisfaction 3	5.945	1.173	6.250	.899	5.761	1.277
Referral match 1	4.155	.893	4.478	.830	3.960	.873
Referral match 2	5.022	.897	5.275	.867	4.870	.882
Referral match 3	5.153	.964	5.416	.926	4.994	.953
Opinion seeking 1	4.041	1.461	4.475	1.353	3.780	1.464
Opinion seeking 2	3.133	1.498	3.484	1.589	2.921	1.400
Opinion seeking 3	3.765	1.539	4.150	1.528	3.533	1.500
Opinion seeking 4	4.118	1.444	4.434	1.417	3.927	1.428
Opinion seeking 5	4.108	1.546	4.522	1.429	3.859	1.562
Opinion seeking 6	3.921	1.535	4.234	1.470	3.733	1.543
Opinion leadership 1	4.859	1.336	4.834	1.388	4.874	1.305
Opinion leadership 2	4.396	1.470	4.509	1.509	4.328	1.444
Opinion leadership 3	4.282	1.527	4.466	1.581	4.171	1.484
Opinion leadership 4	4.363	1.255	4.581	1.219	4.232	1.259
Opinion leadership 5	4.504	1.403	4.828	1.308	4.309	1.423
Opinion leadership 6	4.354	1.364	4.572	1.332	4.222	1.367
ln(Opening weekend box-office revenue)	17.508	1.464	17.772	1.346	17.348	1.509
Movie rating	75.566	9.994	79.522	8.730	73.183	9.958
Gender	.402	.491	.403	.491	.401	.491
Age	31.973	9.470	30.856	9.517	32.646	9.387

Table 4

Composite Reliability, Average Variance Extracted, and Correlations Between Factors

	CR	AVE	Correlations		
			Opinion leadership	**Satisfaction**	**Referral match**
Opinion seeking	.872	.533	.419	.041	.422
Opinion leadership	.858	.550		.152	.342
Satisfaction	.771	.530			.292
Referral match	.808	.586			

Table 5
Parameter Estimates

	Model 1		**Model 2**		**Model 3**	
	No endogeneity correction, no mediation		**No endogeneity correction, with mediation**		**With endogeneity correction and mediation**	
	Parameter estimate	**SE**	**Parameter estimate**	**SE**	**Parameter estimate**	**SE**
Equation 2: WOM referral exposure						
Opinion seeking			.096***	.014	.095***	.014
ln(Opening weekend box-office revenue)			.021**	.011	.023**	.010
Movie rating			.013***	.002	.013***	.002
Gender			.038	.032	.038	.032
Age			-.002	.002	-.002	.002
Intercept			-.957***	.209	-.989***	.197
Equation 3: Satisfaction						
WOM referral exposure			.112	.076	-.957**	.385
Referral match			.238***	.086	.315***	.093
WOM referral exposure * Referral match			.231*	.122	.233*	.122
Movie rating			.034**	.004	.049***	.007
Gender			.176**	.073	.211***	.081
Age			.011***	.004	.007*	.004
Equation 4: ln(WOM referral value)						
Satisfaction			.455***	.030	.455***	.030
WOM referral exposure	.256***	.075	.157**	.069	.156**	.069
Opinion leadership	.442***	.044	.364***	.038	.365***	.038
Movie rating	.025***	.004	.009***	.003	.009***	.003
Gender	-.044	.066	-.140**	.061	-.140**	.061
Age	.014***	.003	.008**	.003	.008**	.003
Intercept	-1.071***	.299	-.953***	.302	-1.240***	.323
Error covariance between Equations 2 and 3					.220***	.078
n	851		851		851	
Log likelihood	-7,420.53		-22,618.19		-22,613.46	
Scaling correction factor	1.498		1.363		1.358	
Akaike Information Criterion (AIC)	14,887.07		45,394.37		45,386.92	
Bayesian Information Criterion (BIC)	14,996.24		45,769.34		45,766.64	
# of free parameters	23		79		80	

* *p* < .1; ** *p* < .05; *** *p* < .01

Table 6

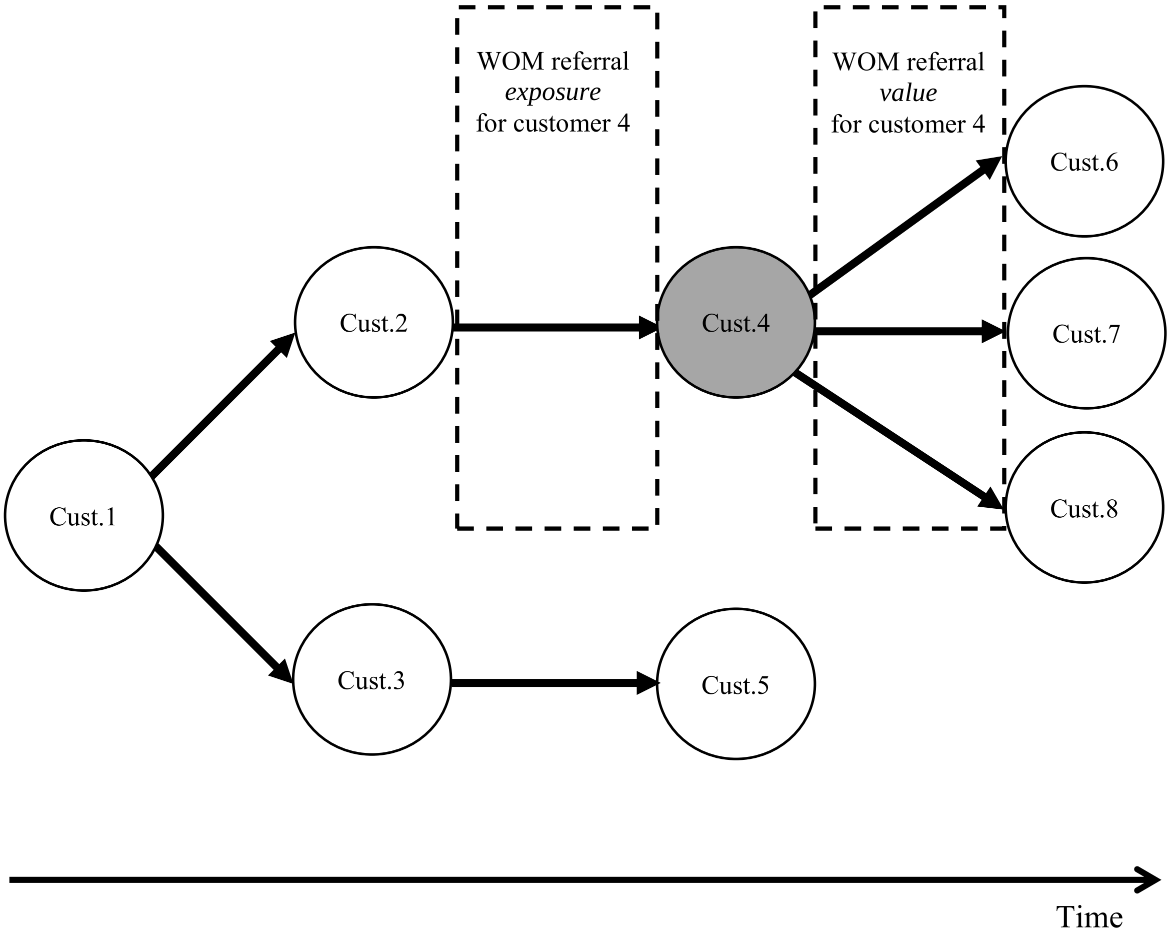
Decomposition of the Total Effect of WOM Exposure on Customer Referral Value, with 95% Bootstrap CIs

	Total effect			Indirect effect			Direct effect		
	2.50%	**M**	**97.50%**	**2.50%**	**M**	**97.50%**	**2.50%**	**M**	**97.50%**
Low referral match (M - 2*SD)	-.877	-.428	-.051	-1.013	-.584	-.224	.022	.156	.294
Mean referral match	-.701	-.279	.073	-.850	-.435	-.105	.022	.156	.294
High referral match (M + 2*SD)	-.586	-.130	.263	-.727	-.287	.093	.022	.156	.294

Note: This table shows the total, indirect (mediation) and direct effects of WOM referral exposure on referral value (based on Model 3 parameter estimates) and their 95% bootstrap confidence intervals (10,000 iterations).

Figures

Figure 1: Visualization of Referral Cascades.



Note: Circles represent customers and arrows indicate referrals. For instance, customer 4 receives a referral from customer 2 and in turn refers to customer 6, 7 and 8.

Figure 2: Theoretical Framework

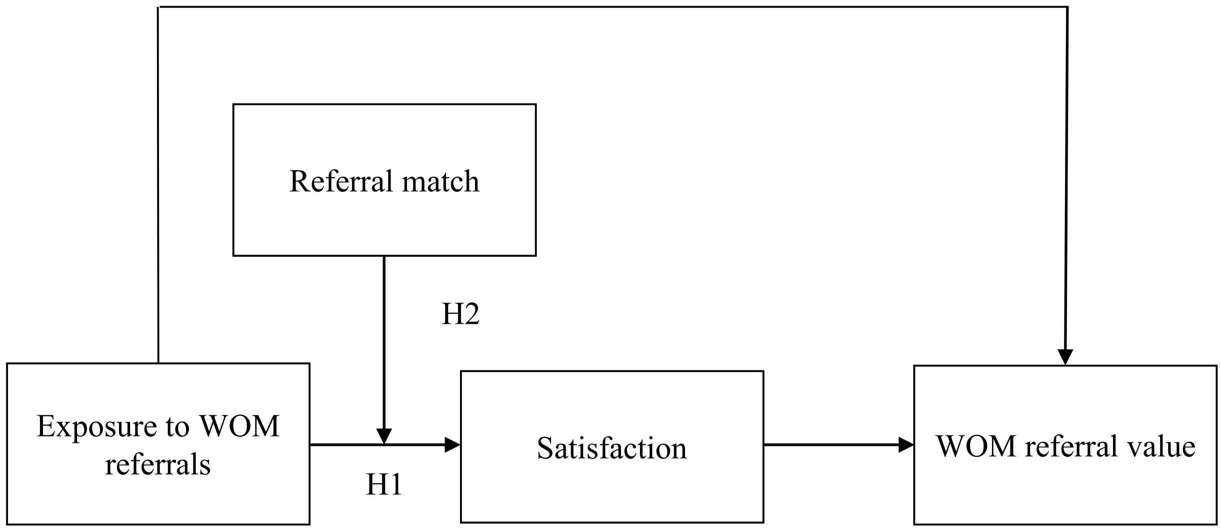
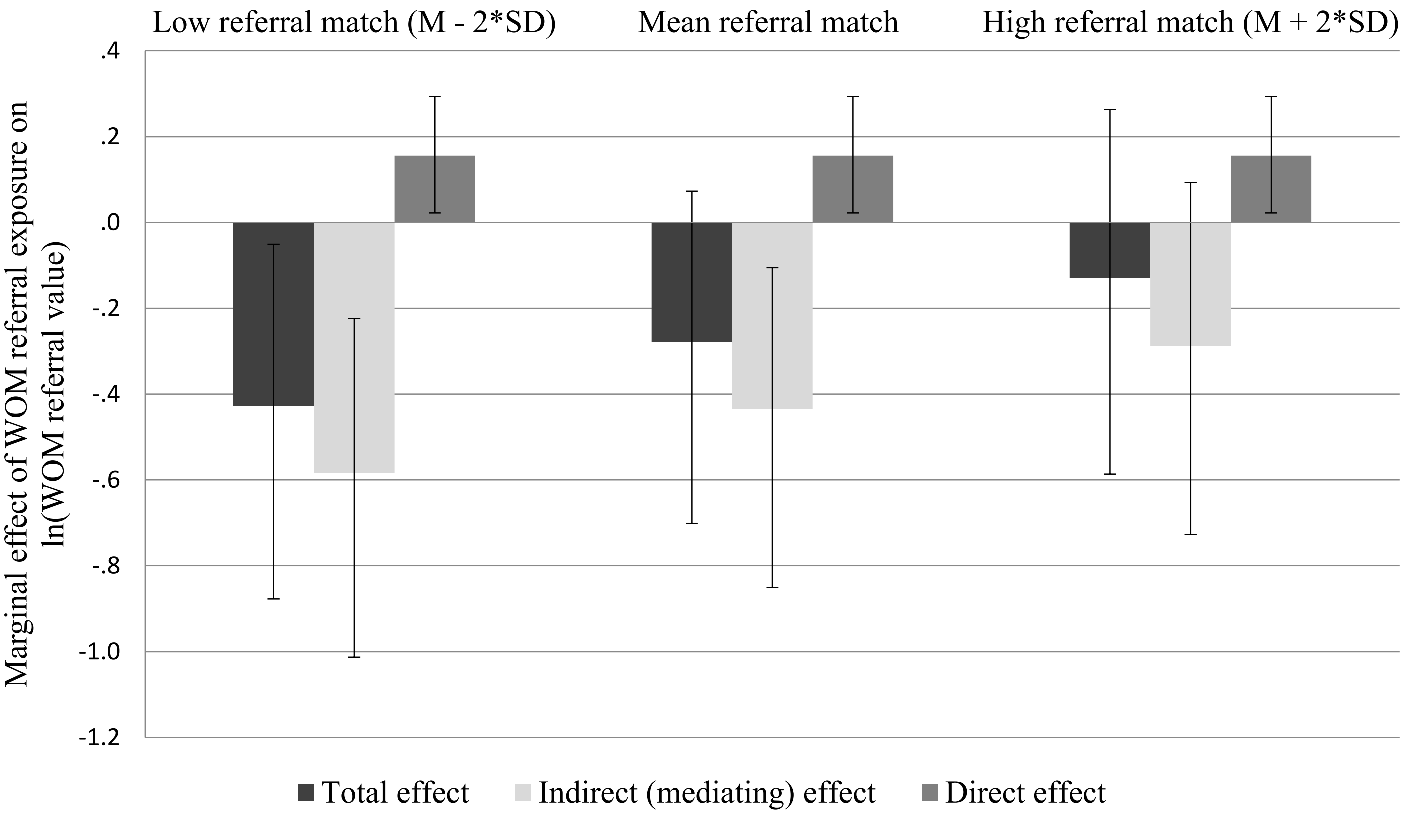


Figure 3: Decomposition of the Total Effect of WOM Exposure on a Customer Referral Value



Note: Error bars denote 95% bootstrap confidence intervals.