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Reward-scrounging in customer referral programs

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ABSTRACT

Rewarding existing customers for the recruitment of new ones has become an increasingly popular acquisition tool for companies. However, when a company rewards the recruitment of a new customer, managers are unaware of whether the rewarded referral was actually necessary or whether "reward-scrounging" has occurred because the referral receiver would have converted anyway. As a consequence, companies risk overestimating the effectiveness of their referral programs, which is why gaining insights into how and when reward-scrounging occurs is crucial. In this study, we employ a large data set from the telecommunications industry to analyze the drivers of reward-scrounging. The results indicate that reward-scrounging reduces the effectiveness of referral reward programs over time and that its likelihood depends on both the referral sender's network position and the company's marketing activities. The findings are used to develop managerial means to alleviate the negative effects of reward-scrounging.

1. Introduction

Each time a new customer is recruited by an existing customer through a company's referral reward program, managers typically face uncertainty about whether the rewarded referral has actually contributed to the purchase decision. In some cases, the rewarded referral may actually lead to conversion, but in other cases, the company's referral reward is not necessary because the referral receiver would have converted anyway. This *reward-scrounging*—namely, the receipt of a reward by an existing customer for recruiting a new customer who would have signed up with the firm, regardless of the rewarded referral—has a substantial impact on the evaluation of a referral reward program because it may also incur high opportunity costs. Such costs are incurred because the money that was spent could have been better invested in the acquisition of as-yet undecided prospects. Given the substantial investment that firms undertake in their referral reward programs (e.g., *American Express* pays $100 for each referred customer, and *AT&T* offers its customers as much as $575 per year for recruited customers), large amounts of money are consequently spent on unnecessary rewards. Furthermore, the effectiveness of the entire referral reward program can be highly overrated if reward-scrounging is neglected. As a result of its importance, measuring the actual value of a referral has already gained attention in the marketing research, and the share of unnecessary rewards has been shown to be substantial—up to 50% (Kumar, Petersen, & Leone, 2010; Libai, Muller, & Peres, 2013).

However, the popularity of referral reward programs has been constantly growing in recent years, and companies from a variety of industries, such as telecommunications, media, banking, and insurance, increasingly value referral programs as efficient tools for

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customer acquisition (Garnefeld, Eggert, Helm, & Tax, 2013; Schmitt, Skiera, & Van den Bulte, 2011). As a consequence of their practical relevance, numerous research studies have investigated various aspects of referral programs. For example, some studies have analyzed the value of referred customers (Armelini, Barrot, & Becker, 2015; Schmitt et al., 2011) and the profitability of referring customers (Garnefeld et al., 2013). Other research has examined optimal reward designs (Biyalogorsky, Gerstner, & Libai, 2001; Kornish & Li, 2010), drivers of participation in referral programs (Claus, Geyskens, Millet, & Dewitte, 2012; Ryu & Feick, 2007; Verlegh, Ryu, Tuk, & Feick, 2013), optimal customers to target (Hinz, Skiera, Barrot, & Becker, 2011; Kumar et al., 2010), and the effectiveness of marketing instruments to stimulate rewarded referrals (Barrot, Becker, & Meyners, 2013; Ryu & Feick, 2007). Although these initial studies provide preliminary insights into the phenomenon (Kumar et al., 2010; Libai et al., 2013) by including reward-scrounging in profitability analyses, marketing research still lacks insights into the specific circumstances under which reward-scrounging occurs and the managerial means that could be used to reduce or to prevent it. Finding such instruments that actively reduce reward-scrounging would be an important step for the profitable management of referral reward programs.

This study contributes to the existing research on referral programs in multiple ways. We developed an empirical model to determine whether a referral receiver (that is, the referred customer) would have converted anyway, and we use the data to analyze multiple drivers that influence reward-scrounging and examine strategies for how companies can use these insights to reduce or prevent reward-scrounging. For our analysis, we employ comprehensive and unique industry data from two competing mobile phone operators that include customer data (such as demographics, profitability, and social networks), referral data, and advertising spending.[1] The results indicate that reward-scrounging reduces the effectiveness of referral reward programs over time, thus making alternative marketing and seeding approaches necessary.

2. Theoretical background

Given that between 20% and 50% of all purchase decisions are based on personal recommendations (Bughin, Doogan, & Vetvik, 2010), companies seek to stimulate and manage word-of mouth (WOM) by providing rewards (e.g., cash, gifts, or free services) for new customer referrals (Garnefeld et al., 2013; Kornish & Li, 2010). Such referral reward programs offer incentives to existing customers to bring in new customers. For instance, the referral program that is analyzed in this study is typical for a mobile phone provider. Here, customers go to the provider's website, type in the name and e-mail address of a prospective customer, and initiate a referral message. Once the receiver reacts to the link and signs up with the provider, the sender of the referral receives a reward (e.g., airtime credit). Alternatively, a prospect can indicate the existing customer from whom he or she received the recommendation during the sign-up process.[2] In both cases, the referral receiver is fully aware that the sender receives a reward for the referral. Hence, we do not encounter issues of negative responses to referrals as a result of undisclosed rewards such as lack of authenticity of the recommendation or the inference of ulterior motives by the referral receiver (Mayzlin, Dover, & Chevalier, 2014; Verlegh et al., 2013).

The benefits of referral programs are widely accepted and have been shown repeatedly in previous studies. For instance, customers who are acquired through referrals are considered more valuable than other customers because they yield a higher contribution margin than customers who are acquired through other channels (Armelini et al., 2015; Schmitt et al., 2011). Similarly, referred customers exhibit a higher willingness to refer people, thus adding to the profitability of referral programs (Gilly, Graham, Wolfinbarger, & Yale, 1998; Von Wangenheim & Bayón, 2004). Several studies also suggest that WOM-induced customers are more loyal than are customers who are acquired through advertising (Schmitt et al., 2011; Villanueva, Yoo, & Hanssens, 2008). The same applies to referral senders, who also yield higher retention rates after engaging in WOM communication (Garnefeld et al., 2013). These direct and indirect effects increase the profitability of referral programs and explain their popularity in marketing practices.

However, the profitability of referral programs may be substantially impaired if companies provide rewards for referrals that actually do not contribute to purchase decisions (Kumar, Petersen, & Leone, 2007; Kumar et al., 2010). In this case, a prospect is very likely to convert irrespective of the rewarded referral, thus rendering the reward unnecessary and causing the profitability of the referral or the entire program to be overrated. Hence, the *reward-scrounging* phenomenon occurs when referral receivers' conversion probability is already high enough to make them purchase the product, regardless of whether the referring customer receives a reward. In such cases, it is irrelevant whether the reward is taken intentionally as a welcome add-on or whether consumers are simply unaware of their preferences, as the reward actually would not have been necessary in either case.

Previous studies in marketing research have already acknowledged the existence of reward-scrounging or similar phenomena in customer referral programs. Focusing on the referral sender's perspective, Biyalogorsky et al. (2001) develop an analytical model and demonstrate that if the level of customer delight is sufficiently high, the customer is likely to recommend a product. In this case, offering a reward would not be necessary because the sender's motivation to spread the word is already high enough. To estimate the customer's referral value, in Kumar et al.'s (2007, 2010) survey, referral receivers were asked to determine whether they would have joined irrespective of the referral. Their results indicate that 50% of all referred customers stated that they would have signed up anyway, which needs to be accounted for in the customer referral value. On a similar note, Libai et al. (2013) divide the overall contribution of WOM seeding campaigns into market expansion and the simple acceleration of adoption. Using simulations that depend on social network structures and different market conditions, they show that on an aggregate level,

[1] The focal product in this study is a prepaid mobile phone plan that includes a per-minute/per-message tariff.

[2] In the following, the two modes are referred to as sender- and receiver-stated referrals. In both cases, the airtime is credited to the account after three weeks. The number of referrals per customer is not limited.

only 65% of the WOM seeding program's value is due to market expansion, whereas 35% should instead be considered acceleration. In other words, although WOM predominantly converts potential non-adopters into customers, it can also accelerate the adoption process for existing prospects.[3] Despite the substantial amount of unnecessary costs and its relevance for management practices, important aspects of the reward-scrounging phenomenon remain unexplored. To the best of our knowledge, no research exists on the specific drivers that influence the individual likelihood of reward-scrounging.

Theoretically, reward-scrounging occurs when a prospect receives a rewarded referral but already had a sufficiently high conversion probability to convert and would have become a customer irrespective of the referral. This formal condition of reward-scrounging is rather useless for firms because the referral receiver is only known after his or her conversion and thus cannot be reached by the company before the referral occurs. For this reason, the managerial means of reducing or preventing reward-scrounging should instead focus on the sender of the referral. Every customer who converts through a company's referral reward program has had—by definition—at least one conversation with the referral sender about the product. Within that conversation, the referral sender spreads the word about the product's features, its advantages, and the company's referral reward program, which they could employ to sign up with the company. Therefore, reward-scrounging is likely to occur (*i*) if the referral sender would recommend the product even without the referral reward and (*ii*) if the referral sender is sufficiently convincing in making the referral receiver follow his or her recommendation, irrespective of whether a reward is paid. This could, for example, occur in a case in which the sender shares similar utility considerations with the receiver (Haenlein & Libai, 2013; Manski, 2000) or possesses a particular experience or expertise in the product category (Moldovan & Goldenberg, 2004). Building on the previous research, we examine different drivers that affect the likelihood that referrals are not only sent but also accepted. To arrive at managerially useful insights, it is necessary to analyze the potential drivers that contain information that is readily available to companies. In this respect, companies can manage the likelihood of referrals that are sent and accepted through two means: targeting the referral sender or using marketing campaigns. In the following sections, we elaborate on how both drivers theoretically affect the likelihood of reward-scrounging.

2.1. Characteristics of referral senders

In the marketing literature, hubs have gained particular attention because of their important role for WOM (Hinz et al., 2011). Hubs are individuals with a large number of social ties (hence, a high network degree) that enable them to easily disseminate information within social networks (Wasserman & Faust, 1994). The previous research has found them to be effective targets for seeding strategies (Hinz et al., 2011) and to have a higher propensity to adopt innovations and, in turn, accelerate the diffusion of new products (Goldenberg, Han, Lehmann, & Hong, 2009). Additionally, hubs possess a high propensity of sending out recommendations and exert high influence on others because they are considered to be opinion leaders and influentials (Iyengar, Van den Bulte, & Valente, 2011; Libai et al., 2013; Watts & Dodds, 2007). Consequently, hub recommendations are more likely not only to occur but also to be followed—irrespective of a rewarded referral.

Furthermore, in addition to the referral sender's more general characteristics regarding network degree and opinion leadership, the likelihood and acceptance of a referral may depend on product-related attributes, such as the referrer's usage patterns. Previous studies show that social contagion is more influential the higher the usage of the referrer, which is particularly true for products with high perceived risks for the adopter. Here, recommendations are more important for convincing peers than for simply creating awareness (Iyengar et al., 2011). Due to heavy users' credible levels of experience with a product, their recommendations are more influential and, hence, more often followed. Furthermore, heavy usage usually occurs when a user is satisfied with a product, which would make a recommendation not only more influential but also more likely (Anderson, 1998; Wirtz & Chew, 2002). Similarly, some studies indicate that the likelihood of referring a product increases with higher customer lifetime values (Barrot et al., 2013; Kumar et al., 2007).

2.2. Marketing activities

Companies can also exert a direct influence on reward-scrounging with their marketing activities. Previous research has shown that advertising increases the conversion probabilities (Iyengar et al., 2011; Prins & Verhoef, 2007) and leads to increased WOM (i.e., the ripple effect; Hogan, Lemon, & Libai, 2004). Furthermore, price promotions simultaneously increase referral likelihood and lower the prospect's adoption threshold (Biyalogorsky et al., 2001; Kornish & Li, 2010). However, marketing efforts not only likely increase the referral quantity, but they also likely affect whether the referral is followed. For instance, advertising may lead to higher brand strength, which consequently reduces the perceived risk for the referral receiver and makes a positive response to a referral more likely (Ryu & Feick, 2007). Similarly, Libai et al. (2013) show that the effect of market expansion through WOM decreases with higher brand strength. Price promotions similarly lead to more positive responses because they reduce the perceived risk for a prospect, which highly impacts whether a recommendation is followed.

Building on these theoretical considerations that have been derived from the previous research on the reward-scrounging phenomenon and the general WOM literature, we use the following empirical study to determine (*i*) what drivers influence reward-scrounging in customer referral programs and (*ii*) how firms can alleviate the negative effects of reward-scrounging. To answer these two research questions, the empirical analysis consists of multiple steps. First, we estimate the individual conversion

[3] We separate the accelerating effect of referral programs on adoption from reward-scrounging in the following analyses as adoption acceleration can provide an additional value for a firm, for example, due to accelerated word-of-mouth, higher market shares at early stages, or a higher valuation during an IPO or investment round.

probabilities for all of the prospects in our sample (*Step 1*) and use them to identify the referral receivers who would have converted without a rewarded referral (*Step 2*). Knowing which referrals can be considered the result of reward-scrounging, we analyze the drivers of reward-scrounging by examining all of the referrals on a dyadic basis (*Step 3*). Finally, we use the results obtained for reward-scrounging drivers to determine the consequences for the overall effectiveness of referral reward programs (*Step 4*) and to analyze targeting strategies to prevent reward-scrounging (*Step 5*).

3. Modelling approach

In the preceding sections, we conceptualized a reward-scrounger as a prospect who chose to join the firm through the referral program, even though he or she would have become a customer of the firm regardless of the referral reward being offered. We can mathematically translate this latter characteristic to the condition that the consumer's firm choice probability is not much affected by the referral program, which in turn can be translated to the condition that the consumer has a low referral program elasticity of choice probability, because low sensitivity to a marketing variable is equivalent to low elasticity for that variable. To identify scroungers, therefore, we select the consumers with low referral program elasticity, high conversion probability, and enrollment through the referral program. This requires us to estimate conversion choice probabilities and elasticities at the level of individual consumers. We do this using a time-inhomogeneous Poisson process with across-consumer heterogeneity. Assume that a prospective customer can choose from a set of firms, taken here for simplicity to consist of just two firms, Firm A and Firm B (the model is more general and can handle as many firms as there are in the data). For each firm, the prospect experiences multiple sources of influence that translate into mental activation events within the prospect's decision process. Receiving these mental activation events causes the prospect to consider signing up for either Firm A or Firm B. An example of such a mental activation event is the viewing of an advertisement from one of the firms or an interaction with a friend who is already a customer of one of the firms. If, during a specific period, the mental activation level that corresponds with a particular firm is sufficiently high and the customer acts on this mental activation, the customer will sign up with that firm. If, during this period, the mental activation level is not high enough for either firm or the customer does not act on this mental activation, the customer will not sign up during the period and advances to the next period. If the prospect decides to convert to one of the firms in a given period, he or she decides based on the volume of mental activation events that corresponds with the respective conversion probabilities for Firm A and Firm B. Hence, the relative conversion probabilities for Firm A and Firm B determine which firm the prospect signs up with (Libai et al., 2013). Firm A's referral reward program follows the theoretical rationale that prospects who would typically decide in favor of Firm B are tilted toward Firm A, despite their otherwise unfavorable conversion probability for Firm A. On the other hand, it would not be necessary to reward the recruitment of a prospect who is already in favor in Firm A (Kumar et al., 2010). To identify these unnecessarily rewarded recruitments, we first estimate a time-varying model to assess the conversion probabilities for Firm A and Firm B and the corresponding referral program elasticities.

Formally, we use the notation v_{itk} to denote the volume of mental activation events that are received by prospect i in time period t that cause him or her to consider signing up with firm k, where k ranges between 1 and K. In our model, we assume that mental activation events arrive via a time-inhomogeneous Poisson process in which, within any one time period, the mental activation events for firm k arrive with exponential inter-arrival times with rate λ_{itk}; these rates can vary with t so that different time periods have different arrival rates. We also assume that any of these mental activation events can result in conversion to either of the firms, with a certain probability that is constant across all of the time periods and firms.

Based on standard theory about Poisson processes, the probability of prospect i not signing up as a customer in time period t, which is conditional on not having already signed up, is $exp(-\sum_{k=1}^{K}\lambda_{itk})$. The reason for this is that the sum of the Poisson random variables is also a Poisson random variable, with an expectation that is equal to the sum of the means of the individual Poisson arrival variables. Therefore, the number of arrivals across all of the firms is a Poisson random variable with a mean of $\lambda = \sum_{k=1}^{K}\lambda_{itk}$. For any Poisson random variable with a mean of λ, the probability of zero arrivals is $\exp(-\lambda)$. This result implies that the probability that customer acquisition will not occur in time period t is $exp(-\sum_{k=1}^{K}\lambda_{itk})$, as given above. A direct implication of the previous point is that the probability that the prospect signs up in time period t, which is conditional on not having already signed up, is $1-exp(-\sum_{k=1}^{K}\lambda_{itk})$. The unconditional probability that the prospect signs up as a customer in time period t is the probability that the prospect does not sign up in any of the preceding time periods 1, 2, … $(t-1)$, multiplied by the conditional probability that the prospect signs up in period t. Combining these two sets of probabilities, we can express the unconditional probability of a prospect signing up as a customer in period t as

$$\left(1-\exp\left(-\sum_{k=1}^{K}\lambda_{itk}\right)\right)\times\prod_{t'=1}^{t-1}\exp\left(\sum_{k=1}^{K}\lambda_{it'k}\right). \tag{1}$$

Conditional on prospect i signing up with any of the firms in period t, we obtain the probability c_{ikt} of the customer choosing to sign up with firm k to be

$$c_{ikt}=\frac{\lambda_{ikt}}{\sum_{k'=1}^{K}\lambda_{ik't}}. \tag{2}$$

These probability expressions follow from standard results in Poisson point processes as described in Ross (2007). The individual level likelihood when we observe the time of choice and the firm that is chosen is the product of expressions (1) and (2). Note that an important feature of the marketing and consumer behavior in the problem context is that the timing and choice depends on the covariates as they evolve over time. The advantage of the time-inhomogeneous Poisson model is that it can accommodate this feature.

For each prospect, we observe the timing of customer acquisitions and the firm choice for the customer acquisitions in our dataset. Therefore, if we know the values of λ_{ikt} for all k for all t until the time of acquisition, we can express the likelihood for these observed data for prospect i. Taking the log of this likelihood and adding it across all of the prospects yields the total data likelihood. Maximizing this log-likelihood yields the maximum likelihood estimates for the parameters. We now describe the parameterization that underlies the values of λ_{ikt}.

When we model the Poisson arrival rate as a function of covariates (see Cameron & Trivedi, 2013), we model each λ value as the exponential of a linear combination of an intercept and time-varying predictors. Assume that the time-varying predictors are represented in x_{itp}, where $p = 1, 2, \ldots P$ indexes the predictor variables. We model λ_{ikt} as

$$\lambda_{ikt} = \exp\left(\sum_{p=1}^{P} \beta_{ikp} x_{itp}\right). \tag{3}$$

Across-consumer heterogeneity: the coefficients β_{ikp} can vary from prospect to prospect, depending on the prospects' background characteristics, which are represented by z_{id}, where $d = 1, 2, \ldots D$ indexes the background characteristics. We model β_{ikp} as

$$\beta_{ikp} = \sum_{d=1}^{D} \alpha_{kpd} z_{id}. \tag{4}$$

This is a hierarchical Bayes model with the prior for each prospect's β governed by the background variables z through the α-factors as interaction factors. We estimate the model using standard methods for hierarchical models.

Using the properties of the Poisson and multinomial logit models, it is easy to show that the elasticity η of the choice probability for firm k with respect to any predictor is

$$\eta = \beta \cdot \left(1 - \frac{\lambda_{ikt}}{\sum_{k\prime=1}^{K} \lambda_{ik\prime t}}\right) \tag{5}$$

where β is the coefficient that corresponds to the x construct or predictor whose elasticity we want to assess.[4]

4. Empirical study

4.1. Data

4.1.1. Industry context

For our analyses, we use a set of unique field data from two competing mobile phone operators offering prepaid mobile phone (talk, text, and data) plans in the German market. In particular, the data for the two companies (Firms A and B) include individual-level information on the customers, their communication, and their referrals, as well as the companies' advertising spending for a 15-month period. The two firms are highly comparable, as they operate in a strongly regulated market where, for example, the key cost component, i.e., the interconnection prices to be paid to the network operators are universally set by state authorities (the German equivalent to the FCC in the U.S.). Consequently, the firms offered the same tariffs (similar pricing) and used the infrastructure of the same network operator (identical network reception and quality).[5] Furthermore, they entered the market for no-frills mobile telecommunication at the same time, i.e., directly after the regulatory authorities opened the market for this business model. During the 15-month observation period that started with both companies' market launches, 75,913 customers joined focal Firm A, and 48,266 joined Firm B, rendering each a considerable double-digit share of this specific market segment at that time.[6] Given the equal price level of all competitors in that market segment, all of the customers who were acquired during that time were either new adopters or they came from competitors with high-priced contractual offers. With respect to switching customers, we observe very few cases (211). In order not to overestimate the conversion probabilities for Firm A or B, we estimated the model with 4792 customers from a competing firm that had neither converted to A nor to B. The competing firm is

[4] Contingent on the approval of the cooperating company, the authors can provide a sanitized version of the code upon request.

[5] Neither company possesses its own network infrastructure, but both companies acquire and resell network capacities from a cooperating network operator. These unique data are available to us because the company that we received the data from acquired the competing firm 15 months after market launch and integrated the competitor's customers into its customer base.

[6] Only one no-frills, low-cost mobile phone provider preceded both companies, albeit less than a month. Eventually, the merged company managed to establish itself at the top of the market segment.

comparable to Firm A and B as it also uses the same network infrastructure and was introduced as a new brand at market launch. Yet, its marketing strategy differed somewhat from Firm A's and B′s by additionally offering tariffs for affordable international calls aiming to be price leader in this segment. By including this data on additional market segments, we account for competition beyond the two focal firms and provide a more realistic and exhaustive market scenario. Technically, this prevents us from overestimating the conversion probabilities for Firms A and B. We use the same information for all of the customers from Firms A and B and the competition.

4.1.2. Customer and communication data

Specifically, the customer data include individual information,[7] such as the exact date of adoption, gender, age, zip code, and purchasing power (per zip code). The communication data contain the customers' call records, which provide information about >100 million outgoing calls and text messages from all customers of both Firm A and Firm B. Aggregating calls and text messages (on individual and dyadic levels) enables us to reconstruct a customer's complete social network, including ties to existing customers and non-customers. The previous studies show that mobile phone data are a highly representative proxy for an individual's real social network and the strength of his or her relationships (e.g., Onnela et al., 2007; Shi, Yang, & Chiang, 2010). Because communication behaviors can only be recorded after conversion, we need to assume that a customer's social network remains constant before and after his or her adoption of the provider. This assumption is reasonable because previous studies indicate that new communication methods do not alter social networks as they remain the same while only the provider changes (Boase, Horrigan, Wellman, & Lee, 2006; Eagle, Pentland, & Lazer, 2009; Rice, 1990).

4.1.3. Referral data

For the referral data, we tracked the referral reward program that Firm A offered immediately after launch. During the 15-month observation period, 19,563 customers participated in the referral program as referral senders (26% of the customer base). Sending out on average 1.3 referrals, 28.5% of the senders participated multiple times in the program. As a consequence, 25,451 individuals converted through the company's referral program, which rendered dyadic information about the sender and receiver of the referral. For each rewarded referral, the referral sender received free airtime which was worth €10. The company offered two different modes of referrals. Existing customers could either invite a friend to join by sending an email with an invitation link to the referral program (sender-stated referrals), or the new customer could name an existing customer as the source of information at the time of conversion (receiver-stated referrals). While 77% of the referrals were sender-stated, only 23% were receiver-stated. The reward was identical for both referral modes. Neither Firm B nor the competing company used a referral reward program.

4.1.4. Advertising data

Furthermore, we tracked both companies' complete advertising spending during the observation period. In particular, we observed the companies' spending per month for each advertising medium (e.g., a specific TV channel, newspaper, radio station, or website) and used it to estimate the conversion probabilities. Given that both companies' advertising was geographically dispersed during the observation period, we captured this heterogeneity by matching the advertising data with the regional reach of each medium as published in their media planning data. Consequently, we were able to capture the regional dispersion by using the advertising spending per month at the zip code level.[8]

4.2. Estimating individual conversion probabilities (Step 1)

4.2.1. Variables and measures

We estimate conversion probabilities using the methodology that is described in Section 3. In our empirical analysis, the x variables correspond with eight time-varying predictor terms (four for each firm) that are expected to affect the prospect's decision to sign up with one of the two firms. The local penetration rate ($LocalPenetration_{itk}$) is the number of existing customers in a potential customer's zip code area per 1000 inhabitants and per month. We use the local penetration rate because social contagion outside of the customer's directly observable network is most likely to occur within geographic proximity (Hägerstrand, 1967) and has been shown to be a strong indicator for social contagion effects in previous studies (e.g., Manchanda, Xie, & Youn, 2008). The potential customer's exposure to existing customers ($Exposure_{itk}$) is measured as a time-varying covariate that aggregates the number of ties a potential customer has to existing customers of firm k in the prospect's social network in each month until conversion. For the month of conversion, we measure the exposure on a daily basis to prevent network autocorrelation (Manski, 1993). To capture the qualitative aspect of the relationship with the existing customers and the associated intensity of social contagion (Brown & Reingen, 1987; Ryu & Feick, 2007), we analyze the tie strength to existing customers ($TieStrength_{itk}$) based on their communication intensity. We employ the approach of Nitzan and Libai (2011) and measure the tie strength between customer i and each of his contacts as the airtime of the respective dyad divided by the total airtime of customer i. In our model, we use the sum of the tie strength with all of the existing customers at time t in customer i's social network. The fourth predictor is advertising

[7] The protection of consumer privacy has been ensured by encrypting sensitive data, such as the customers' names and phone numbers, twice (by the network provider and the authors) to prevent any form of backtracking.

[8] The approximately 8000 zip code areas with an average of 10,000 residents signify the lowest possible aggregate level in Germany.

($Advertising_{itk}$), as a measure of the companies' advertising spending per 1000 residents, zip code, and month with a temporal carry-over effect that is modeled as a geometrically distributed stock variable (Hanssens, Parsons, & Schultz, 2001).

In our empirical analysis, the z variables correspond to the four background variables of each prospect that research agrees strongly influence adoption decisions: the prospect's gender, age, purchasing power (Dickerson & Gentry, 1983; Greve, Strang, & Tuma, 1995; Rogers, 2003), and social network degree (Goldenberg et al., 2009; Harrigan, Achananuparp, & Lim, 2012). An overview of all of the variables, descriptive measures, and correlations is provided in Table 1.

4.2.2. Results

The estimates of the β-coefficients for our empirical illustration are reported in Table 2, which provides the value of each β_{ikp} averaged across all of the prospects i. The estimates of the α-coefficients for our empirical illustration are listed in Table 3. We report the intercepts of the α-coefficients to illustrate their direct impact on the conversion decision. The coefficients for all of the interactions with the β-coefficients are reported in Appendix A.

The coefficients can be interpreted such that increasing the value of a covariate by one standard deviation increases log(λ) by the respective effect strength. The total results are plausible and, according to the theoretical expectations about the α- and β-coefficients and the influence of the time-varying variables (e.g., exposure, tie strength, local penetration, or advertising for the two firms), comply with traditional adoption and diffusion theory.

The estimated coefficients and the prospect's covariate values enable us to compute individual conversion probabilities for each prospect, month, and firm. Thus, for each prospect during their conversion month, we compute the probability of his or her conversion to Firm A or Firm B, conditional on the decision to convert to either of the firms in that month. Because both conditional probabilities add up to one, for each prospect, we observe whether his or her conversion probability favors Firm A or Firm B and which firm they actually choose. Overall, the model shows a good prediction fit because 70% of all of the prospects are correctly predicted according to their actual choice.

We capture the insensitivity of a prospect to the referral program through the individual level conversion probabilities and the referral program elasticity expression given in Eq. (5). For a prospect with low elasticity for a certain firm, the referral program does not much impact the decision to enroll with that firm. Note that Eqs. (2) and (5) imply that prospects with higher conversion probability will have lower elasticities.

4.3. Determining reward-scrounging referrals (Step 2)

As elaborated in the theoretical background and in Section 3, the formal condition for a referral to be considered to be a reward-scrounging referral is that there be sufficiently low referral program elasticity of choice (or a equivalently a low influence of the referral program on the consumer's choosing the firm). For this purpose, we choose those consumers for whom the elasticity is <0.001 and conversion probability is >0.99. Given this very conservative threshold, it is highly reasonable to assume that the referral receiver would have signed up with Firm A anyway, meaning that the referral can be considered to have been the result of reward-scrounging.

The results indicate that the share of reward-scrounging among all new referrals increases continuously over time to nearly 35% in month 15. On average, approximately 17% of the referral receivers would have converted to Firm A regardless of the rewarded referral across the 15 months. From the firm's perspective, this finding means that for 17% of all of the referrals, the reward was not necessary and could have been invested more efficiently elsewhere because these customers would have chosen Firm A anyway. The extent of the reward-scrounging that we find with our empirical model is consistent with the related studies that have used other methods. By surveying customers after conversion, Kumar et al. (2007, 2010) find that up to 50% of all referral receivers did not make purchases because of the referral. Similarly, in line with our findings, Libai et al. (2013) show that 35% of WOM does not lead to market expansion.

Comparable to levels of significance, the elasticities and conversion probabilities as a threshold for determining reward-scrounging can be considered to be at a level of certainty for whether the prospect would have converted irrespective of a referral. While the conversion of 0.99 is rather conservative, lower thresholds (e.g., 0.90 or 0.95) could be used that would naturally change

Table 1
Descriptive measures and correlations.

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. Exposure firm A[a]	0.18	0.49	1.00										
2. Tie strength firm A[a]	0.03	0.10	0.60	1.00									
3. Exposure firm B[a]	0.06	0.27	−0.04	−0.04	1.00								
4. Tie strength firm B[a]	0.01	0.07	−0.05	−0.04	0.49	1.00							
5. Degree	36.74	37.40	0.10	−0.03	0.05	−0.03	1.00						
6. Gender (1 = female)	0.40	0.49	0.08	0.08	0.04	0.05	−0.03	1.00					
7. Age	42.33	12.48	−0.01	0.02	0.01	0.03	−0.20	−0.05	1.00				
8. Advertising firm A[a]	6.39	7.09	−0.07	−0.05	−0.04	−0.02	0.01	−0.01	0.02	1.00			
9. Local penetration firm A[a]	0.69	0.62	0.24	0.16	0.05	0.00	0.02	0.04	−0.06	−0.19	1.00		
10. Advertising firm B[a]	6.94	9.53	−0.11	−0.08	−0.07	−0.03	0.02	−0.03	0.02	0.28	−0.34	1.00	
11. Local penetration firm B[a]	0.50	0.37	0.08	0.06	0.15	0.09	0.02	0.04	−0.02	−0.19	0.45	−0.35	1.00
12. Purchasing power[b]	17.01	2.64	−0.01	−0.01	0.00	−0.01	−0.01	0.01	0.07	0.08	0.04	0.04	0.09

Table 2
Coefficients of the predictor variables (β coefficients).

	Conversion firm A		Conversion firm B		Conversion competition	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Intercept	−3.887*	0.051	−3.742*	0.065	−15.344*	0.794
Local penetration firm A	0.275*	0.015	−0.306*	0.031	−0.044*	0.067
Exposure firm A	0.121*	0.014	−0.552*	0.086	−0.646*	0.274
Tie strength firm A	0.023*	0.003	−0.485*	0.178	−1.465*	1.478
Advertising firm A	0.080*	0.022	−0.035*	0.029	0.295*	0.444
Local penetration firm B	−0.136*	0.019	0.483*	0.019	−0.031*	0.084
Exposure firm B	−0.110*	0.033	0.075*	0.015	−0.684*	0.599
Tie strength firm B	−0.287*	0.067	0.078*	0.016	−1.564*	2.087
Advertising firm B	−0.088*	0.022	0.044*	0.024	−0.266*	0.766

All predictor variables other than the intercept are standardized to be of mean 0 and variance 1; $N = 128{,}971$; $T = 15$.
* $p < 0.01$ (two–sided significance levels).

the absolute level of reward-scrounging (see Appendix B). However, we find that none of our findings on the drivers of reward-scrounging are sensitive to the chosen threshold. Managerially, the decision which threshold level to choose should be taken based on the ratio between the reward and the customer value and the associated monetary risk of misattributing the referral. The greater the reward compared to the customer value that a (allegedly) referred customer contributes (high risk), the lower should be the threshold in order to ensure the profitability of the program. In case of very low referral rewards (low risk), a conservative threshold (such as the 0.99 that we suggest) can be used as the costs of rewarding a conversion unnecessarily are not high enough to justify means that might prevent a potential prospect from joining.

4.4. Testing the drivers of reward-scrounging (Step 3)

4.4.1. Modelling approach

Having determined which rewarded referrals can be considered to be the result of reward-scrounging, we can analyze which drivers influence the likelihood of reward-scrounging. We estimate a logistic regression model for all 25,451 of the referrals that occur in the first 15 months with reward-scrounging as a dichotomous dependent variable and include a number of predictors to cover the referral sender's as well as the dyad's characteristics, marketing variables, and referral characteristics. Specifically, we include the referral senders' network degree, homophily,[9] tie strength as well as their average revenue per month. Furthermore, we control for the number of referrals that they have sent out, their age, and their gender. To test the impact of marketing efforts on reward-scrounging, we examine the influence of specific advertising campaigns or promotions in the month in which the referral receiver converts. A promotion campaign was such that the converting customers received higher initial airtime if they decided to sign up with Firm A. For advertising campaigns, we include an advertising dummy variable if the advertising expenditures were at least twice as high in the month of conversion as in the preceding month. Additionally, we analyze the impact of the specific referral mode on the prospect's conversions—that is, whether prospects are proactively invited by the referrer or whether they simply state at conversion that they have been referred. Finally, we include a variable that captures the number of months that have passed between market launch and the time of referral to analyze how the likelihood of reward-scrounging develops over time and to control for the for the number of active customers of firm k over time. Appendix C provides an overview of the specific operationalization of each variable.

4.4.2. Results

Table 4 shows the results of the logit model. Overall, the estimated model indicates a reasonable fit with a *pseudo-*R^2 of 19%. With respect to the referral sender characteristics, the results show that both the sender's network degree ($\beta_1 = 0.347$; $p < 0.01$) and the referrer's usage ($\beta_4 = 0.088$; $p < 0.01$) significantly increase the probability that the referral can be considered to be the result of reward-scrounging. Comparing the effect strengths, usage has a much lower effect than the network degree, which shows that the referral sender's general traits seem to be more important than the product-related characteristics. However, in the case of mobile operators, the two concepts are also likely to be interrelated because customers with a high degree are more likely to use their phones to communicate with their large number of social ties. Analogously, the social closeness between sender and receiver is highly influential. The results indicate that both tie strength ($\beta_3 = 0.725$; $p < 0.01$) and homophily ($\beta_2 = 0.370$; $p < 0.01$) strongly affect reward-scrounging. Considering the higher likelihood to follow recommendations from socially close contacts (e.g., due to more intense communication or similar tastes), the results are in line with our expectations based on previous literature.

[9] Homophily refers to the degree of similarity between two individuals, in this case the sender and receiver of the referral (Kossinets & Watts, 2009; McPherson, Smith-Lovin, & Cook, 2001). Specifically, we operationalized homophily following the approach of previous studies (Nitzan & Libai, 2011; Risselada, Verhoef, & Bijmolt, 2014) by using a multidimensional construct in which sharing the same gender, the same age (±5 years), and the same network degree (±10 ties) are each binary coded, weighted by one third.

Table 3
Interaction of the α coefficients with the intercept.

	Conversion firm A		Conversion firm B		Conversion competition	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Gender	–0.061*	0.020	–0.046*	0.029	–0.331*	0.570
Age	0.021*	0.020	0.142*	0.029	–0.533*	0.485
Purchasing power	0.012*	0.020	–0.048*	0.027	0.073*	0.439
Degree	–0.004*	0.023	0.015*	0.025	–1.128*	0.766

All predictor variables other than the intercept are standardized to be of mean 0 and variance 1; $N = 128{,}971$; $T = 15$.
* $p < 0.01$ (two–sided significance levels).

With respect to marketing campaigns, we find that advertising campaigns ($\beta_5 = 0.107$; $p < 0.01$) significantly increase the likelihood of reward-scrounging; however, sales promotions ($\beta_6 = -0.019$; $p > 0.05$) do not. Similar to referral sender traits, marketing campaigns increase both the likelihood and the influence of WOM, but it also lowers the adoption threshold of referral receivers, which has a strong effect on the likelihood of reward-scrounging. Here, companies should be well aware that marketing campaigns can be considered to be a double-edged sword in the context of referral reward programs. On the one hand, they increase the number of acquired customers, but on the other hand, they also increase the likelihood of reward-scrounging. These campaign effects should thus be accounted for to more precisely assess the actual impact of the campaigns.

Another driver of reward-scrounging seems to relate to time, that is, the months that have passed between the Firm A's launch and the time of a referral ($\beta_7 = 0.132$; $p < 0.01$). This implies that the larger the customer base grows over time, the more likely the referral will be considered to be reward-scrounging. The same applies to learning processes that referral senders go through—more and more senders become aware of the reward program as time goes by. With respect to the formal referral mode, the full model does not indicate a significant effect.

In the described (full) model, we integrate two key variables of tie strength and homophily that require information on the nature and intensity of the relationship between a referral sender and receiver. However, such data are not accessible in most industries other than telecommunications (as in our case) where such data can be derived from the provided services. Thus, we estimate a second model that excludes the dyadic relationship variables. While the effects for key variables such as network degree, usage, time, and advertising and/or promotion campaigns remain stable, the results show that in the absence of information on tie strength and homophily the referral mode plays an important role ($\beta_8 = -0.184$; $p < 0.01$), which is particularly interesting from the managerial perspective. As described in the data section, the firm offered two commonly used modes of referral, namely, existing customers sending out invitations to join (sender-stated referrals) or new customers simply naming a referral sender at the time of their conversion (receiver-stated referrals). Apparently, sender-stated referrals have a lower reward-scrounging likelihood than receiver-stated referrals (on average, we observe 18% scrounging for sender- and 26% for receiver-stated referrals). A possible explanation for the difference between the two referral modes could be in the level of awareness each mode actually creates. For this, sender-stated referrals are more appropriate due to the higher threshold of sending out a referral. A sender of a referral needs to be relatively certain that the receiver is not a customer yet and that she has not received a referral invitation from someone else. Thus, customers are more likely to send out referrals if they are convinced to be the only possible source of referral, i.e., if no one else in the network of the receiver has adopted yet. At the same time, such a receiver without (several) adopters in his ego-network is very unlikely to adopt without an active referral, i.e., has a very low probability of scrounging. In contrast, allowing prospects to simply name a referral sender during the purchase process seems to increase the likelihood that the reward

Table 4
Logit models for the drivers of reward-scrounging.

		Beta	SE	Beta	SE
Network degree	β_1	0.347*	0.019	0.277*	0.018
Homophily	β_2	0.370*	0.020		
Tie strength	β_3	0.725*	0.017		
Usage	β_4	0.088*	0.019	0.116*	0.018
Advertising campaign	β_5	0.107*	0.037	0.124*	0.034
Promotion campaign	β_6	−0.019	0.037	−0.021	0.034
Time†	β_7	0.132*	0.005	0.131*	0.005
Referral mode	β_8	−0.007	0.041	−0.184*	0.037
Multiple referrals	β_9	0.006	0.018	−0.089*	0.023
Age	β_{10}	−0.002	0.018	0.064*	0.017
Gender	β_{11}	−0.028	0.038	−0.034	0.031
Constant term	β_{12}	−2.964*	0.071	−2.666*	0.065
LR Chi^2 (df)		4879.03 (11)		1724.66 (9)	
Pseudo–R^2		0.19		0.07	
Observations		25,451		25,451	

Degree, homophily, tie strength, usage, and age are standardized to be of mean 0 and variance 1.
DV = reward-scrounging = 1.
* $p < 0.01$.
† Number of months between market launch and time of referral.

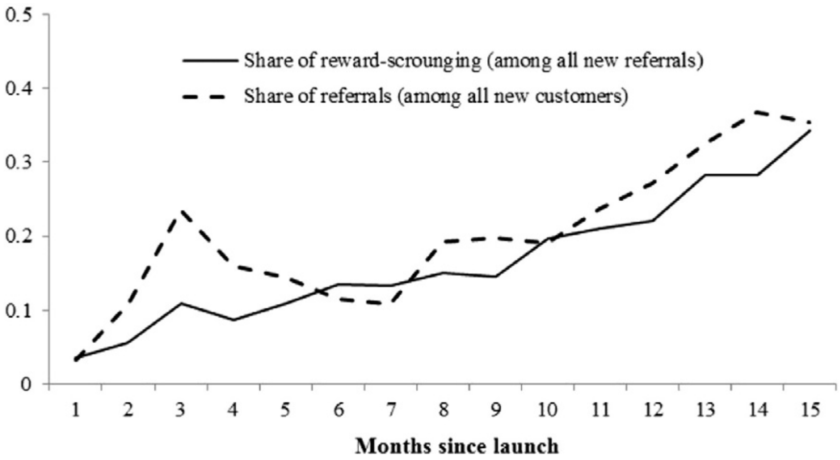


Fig. 1. Development of referrals and reward-scrounging over time. Note: The bases for the share of reward-scrounging are all new referrals and for the share of referrals all new customers of the respective month.

is mainly taken as an add-on. A reason for this could be that customers are actively made aware of the referral program by the question within the conversion process. Here, it is possible that the actual decision was already made in advance, and the likelihood of reward-scrounging thus increases.

4.5. Examining the effectiveness of the referral program (Step 4)

The results in Table 4 indicate a strong positive influence of the time that has passed since the launch on the likelihood of reward-scrounging. To investigate the influence of time in greater detail, we calculate the share of reward-scrounging among all new referrals for each month since the market launch.

The share of reward-scrounging in Fig. 1 clearly demonstrates that the average value of 17% (see Section 4.4.) is not a static value; instead, it increases over time. In the first few months after the launch, the average share of reward-scrounging among all new referrals is very low, which indicates that rewarded referrals are particularly effective during the early months of the diffusion process. While the conversion probability is typically quite low in the early months, rewarded referrals can help to both create awareness and recruit customers who would not have joined otherwise. Consequently, with more customers who are aware of the referral reward program (either from a learning process or from own experience), the share of referrals of the total number of new customers increases over time (see dotted line in Fig. 1). However, the larger the number as well as the share of referral senders, the more a reward can be considered to be unnecessary—the word has already been spread about the brand, and potential customers are more likely to convert without receiving referrals. Hence, the level of referral-scrounging increases. The increasing level of reward-scrounging is in line with the effect that is found by Libai et al. (2013), who show that the ratio of market expansion and acceleration changes over time in WOM seeding programs. That is, the effectiveness of WOM campaigns for product diffusion depends heavily on the time that has passed since a launch (Peres, Muller, & Mahajan, 2010).

Of course, the overall effectiveness of referral reward programs does not only depend on the number of referrals that are triggered by the program but also on the customer value that is generated by the referral receivers (Schmitt et al., 2011). However, if the revenues could have also been generated without the referral, the customer value should not be used to measure the overall profitability of the program and would have to be discounted (Kumar et al., 2010). For instance, Fig. 1 shows that after the 15-month period, the share of reward-scrounging referrals among all new referrals has reached approximately 35%, which is substantial. Surpassing a certain level of reward-scrounging can turn the entire referral program into an unprofitable investment. In that case, managers should be well aware of the elapsed diffusion time and the company's market position and consider only employing referral programs to establish new brands in the market. If the brand has reached a certain position compared with its competitors, terminating the referral program might be more profitable because no money would be wasted on unnecessary rewards and could be more efficiently invested elsewhere.

4.6. Analyzing targeting strategies to reduce reward-scrounging (Step 5)

4.6.1. Targeting based on centrality

As mentioned above, hubs are typically the most desirable customers to target for WOM campaigns due to their innovativeness and their wide reach in their respective social networks (Hinz et al., 2011). However, the results in Table 4 indicate that the referral sender's network degree is among the strongest drivers of reward-scrounging in referral programs. Targeting hubs for referral reward programs apparently involves a trade-off because a wide reach also introduces a risk of high levels of reward-scrounging. Especially in the early stages of the diffusion process, managers typically seek to quickly maximize the number of new customers, for which hubs are particularly useful (Goldenberg et al., 2009).

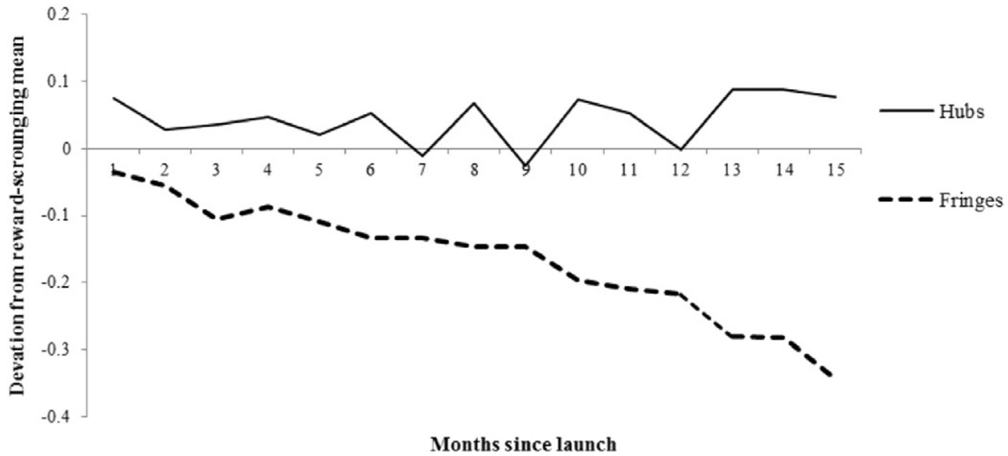


Fig. 2. Reward-scrounging over time, dependent on referral sender's degree.

For this reason, we investigate how reward-scrounging develops over time, depending on the sender's network degree. We focus on the sender's network degree because it is the strongest driver of reward-scrounging and because it is the most applied and examined targeting strategy (Hinz et al., 2011; Libai et al., 2013). To define hubs (high network degree) and fringes (low network degree), we use the actual distribution of network degree in our sample. Specifically, hubs are defined as all customers who have a network degree that is greater than or equal to the 90th percentile of the entire sample, and fringes are defined as customers who have a network degree of less than or equal to the 10th percentile. Fig. 2 displays how the share of reward-scrounging develops over time for these two groups of referral senders. Please note that the graphs show the deviation from the overall reward-scrounging share, as shown in Fig. 1.

Fig. 2 indicates a remarkable development: whereas the share for hubs constantly deviates approximately 5% above the mean, the development for fringes differs substantially. Not only does the share for fringes deviate constantly below the mean in the first months after launch; it also drops considerably in the later months. Therefore, in the later months when the share of reward-scrounging becomes substantial, it could be efficient for companies to target the fringes instead because the level of reward-scrounging is lower.

4.6.2. Integration of referral probability

However, for the targeting of the fringes to be more profitable as a targeting strategy in the later months, the positive effect of the lower likelihood of reward-scrounging needs to outperform the fringes' typically lower referral probability relative to that of the hubs. For this reason, we run a simple simulation to compare both targeting strategies and use the number of actually acquired customers as the target variable, that is, all of the customers that were recruited through the program whose referrals cannot be considered to have engaged in reward-scrounging. For the simulation, an equal number of hubs and fringes are targeted in each month, starting with 10,000 customers in the first month and accounting for an average monthly growth of the customer base of 10%. The empirical reward-scrounging probabilities for the hubs and fringes are taken from our analysis above. The participation rate for the hubs and fringes that we assume for our simulation is based on the previous research on participation and referral rates in referral program campaigns, depending on degree centrality (Hinz et al., 2011). The average rate of successful referrals as a result of a referral targeting campaign is shown to be 2%; however, the hubs are more likely to participate in referral programs, and they refer more customers than the fringes. Therefore, for our simulation, we assume participation rates of 2.5% for the hubs and 1.5% for the fringes.

The left-hand side of Fig. 3 shows the number of acquired customers if reward-scrounging is neglected by the company, and the right-hand side accounts for the actual reward-scrounging share of the hubs and the fringes.

The comparison of the two graphs clearly shows both the difference between the two targeting strategies and the importance of accounting for reward-scrounging. Neglecting reward-scrounging would lead to ostensibly higher numbers of acquired customers if the hubs were targeted due to their higher referral probability, independent of the time that has passed since the brand's launch. Accounting for reward-scrounging, however, indicates a shift in terms of which targeting strategy is more effective. In the early months of the diffusion process, the hubs' higher referral probability compensates for the higher level of reward-scrounging that is induced by the referrals that are sent out by the hubs. However, when the overall share of reward-scrounging increases steeply and the deviation for the fringes drops substantially, targeting the fringes will ultimately outperform the strategy of targeting the hubs. By targeting the fringes, the level of reward-scrounging is kept low, which, in turn, increases the number of customers that are actually acquired by the rewarded referral.

5. Discussion

The objective of this study was to investigate reward-scrounging in referral programs and to analyze its drivers and the managerial possibilities to reduce or to prevent it. Based on a large set of field data from two competing firms, the study yields a

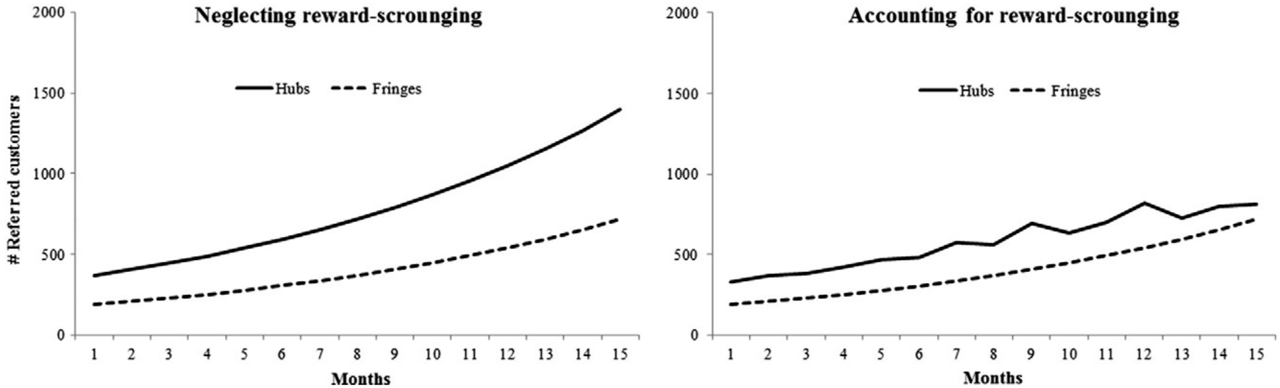


Fig. 3. Number of referred customers by targeting strategy and the months since launch. Note: The targeting simulation is based on 10,000 customers in month 1, a growth rate of the customer base of 10%, referral rates of 2.5% for hubs and 1.5% for fringes (based on Hinz et al., 2011), and the empirically determined reward-scrounging probabilities for hubs and fringes in each month.

number of important contributions for marketing research and practice. First, the study shows that hubs' referrals increase the likelihood of reward-scrounging and discusses how companies' targeting strategies can be adjusted over time. Second, our analyses indicate that referral reward programs become less effective as more time passes from the market launch. Third, the findings reveal that a company's marketing activities can be a double-edged sword in the context of referral reward programs because they increase not only new customer acquisitions but also the likelihood of reward-scrounging. Fourth, this study yields additional insights into reward-scrounging drivers and how they can be used to managerially reduce reward-scrounging.

5.1. Reward-scrounging and network degree

With respect to the influence of hubs, the results indicate that the referral sender's network degree significantly increases the likelihood of reward-scrounging. Whereas marketing research has mainly highlighted the positive aspects of central customers in terms of the likelihood of referrals (Hinz et al., 2011; Libai et al., 2013), this study extends the literature by revealing a downside of using hubs for rewarded referrals. By including reward-scrounging in the analysis, future research should account for the flipside of using influential customers when studying seeding and targeting strategies in the WOM context. From a managerial perspective, these findings are also highly relevant because companies should be aware of the negative aspects of targeting hubs. Our analyses demonstrate how targeting strategies can be adjusted over time to acquire the greatest number of customers without investing a considerable amount of money on unnecessary rewards. Because hubs are more likely to make referrals with high reward-scrounging probabilities (see Fig. 2), especially in the later stages of diffusion, companies should consider targeting other customers (e.g., fringes) who send out referrals with low reward-scrounging probabilities (Kumar et al., 2010). Adjusting the targeting strategy by considering the time since a product's launch or a company's market position may considerably increase the effectiveness of referral targeting campaigns, whereas neglecting reward-scrounging may result in a biased assessment of the effectiveness of targeting strategies. Adapting and applying the right targeting strategy is relatively straightforward because referral reward programs are typically advertised using direct marketing, and companies can use their available customer data to target newsletters, text messages, or other individual channels. To further reduce the reward-scrounging likelihood among hubs, companies could also limit the number of rewarded referrals per sender. This recommendation finds further support if one analyzes reward-scrounging for customers with multiple referrals. While the reward-scrounging likelihood for the first referral is relatively low (17%), it increases substantially for the following referrals (31%).

5.2. Reward-scrounging and referral reward program effectiveness

Irrespective of the targeting strategy, the results indicate a relationship between reward-scrounging and the stage in the diffusion process, which affects the effectiveness of the program over time. In the early months after the launch, nearly all of the referrals are actually effective, and most referral receivers would not have converted otherwise; however, this ratio changes considerably over time. Considering that similar phenomena have been found by Libai et al. (2013), who show that the market expansion through WOM decreases over time, marketing research and practice should consider this issue to a greater extent in the analyses of referral reward programs. Here, it is necessary to question when a referral program is useful, which requires an analysis of a company's market position and the time that has elapsed since a product's launch. To what extent reward-scrounging can be tolerated also depends on the ratio of rewards to revenues because the referral rewards represent the financial investment that is needed to acquire a customer who generates the revenues that justify that investment (Schmitt et al., 2011). If a referral reward is fairly low, reward-scrounging can be considered to be a minor problem. In this case, stopping the referral program altogether would mean losing a high number of profitable new customers who would not convert otherwise. However, the referral reward often represents a substantial share of the expected gross margin, for instance, in the publishing or mobile operator industry. Here, surpassing a certain level of reward-scrounging can turn the entire referral program into an unprofitable investment. Managers should then consider cancelling the program or reducing its reach (e.g., by limiting the number of rewarded referrals per sender). Alternatively, companies may adjust the size of the reward to restore the initial return on investment, which allows for higher tolerance levels of reward-scrounging.

5.3. Reward-scrounging and advertising influence

With respect to the *influence of marketing campaigns*, the findings demonstrate that reward-scrounging increases with companies' advertising campaigns. Although an increase in the advertising spending can generate more customers, it may also increase the number of reward-scrounging referrals during an advertising campaign. The double-edged sword of increasing marketing expenditures in the context of referral reward programs not only extends the literature on referral programs but is also relevant for future research and management practices that seek to measure marketing effectiveness. A holistic perspective thus needs to be applied if companies employ referral reward programs, and they should perform effectiveness analyses of advertising campaigns or sales promotions to prevent biased and overrated assessments of their marketing campaigns. As a consequence, marketing managers should, for example, try to reduce the overlap of regular advertising or promotion activities and referral-reward-programs with regard to the timing of campaigns or the targeted demographics.

5.4. Further drivers of reward-scrounging

With respect to further drivers of reward-scrounging, our analysis on the drivers of reward-scrounging yields managerial means that can be employed to reduce or prevent reward-scrounging. For instance, from a managerial perspective, an interesting finding involves the referral mode that the company offers (sender-stated or receiver-stated referrals). A new customer simply naming his or her source of influence at the time of conversion yields significantly higher probabilities of reward-scrounging than active invitations from existing customers. With receiver-stated referrals, converting prospects likely become aware of the referral program only at time of the conversion and proactively invite friends as a potential referral sender. By eliminating receiver-stated referrals, companies can easily use this study's findings to reduce the share of reward-scrounging, and the risk of losing any potential customers is quite low.

5.5. Limitations and avenues for further research

We acknowledge that our study has some limitations. First, our results are based on two companies from a service industry, which is not uncommon for studies that use extensive proprietary industry data (e.g., Nitzan & Libai, 2011; Schmitt et al., 2011). Although the mobile operator industry follows the same economic principles as other subscription-based industries, our study should be replicated to evaluate whether drivers of reward-scrounging and its consequences vary between companies and industries. For instance, the perceived risk for the referral receiver may influence the actual impact of rewarded referrals (Iyengar et al., 2011). Rewarded referrals are less likely to be crucial conversion factors for high-risk products, such as insurance or financial products. For these products, WOM is likely to occur anyway because prospects proactively request information about existing customers' experiences. In this case, rewards will probably not tip the scale toward a product; they are instead considered to be a welcome addition. However, low-risk products may be less affected by reward-scrounging because a reward is more likely to actually trigger conversion due to the low cost of failure. In this regard, how reward-scrounging relates to pricing as a managerial factor that determines product risk should be investigated.

Second, our study only analyzes reward-scrounging with one specific reward design and size. Because both aspects can differ in referral reward programs (Kornish & Li, 2010; Ryu & Feick, 2007), an examination of how the design and size of rewards influence the drivers of reward-scrounging would be beneficial. For instance, greater rewards may trigger more purchases which may decrease reward-scrounging in a program. However, greater rewards may also incentivize opportunistic behaviors in the form of deliberate reward-grabbing. The reward's design (i.e., rewards for the referral sender and receiver or rewards for only the sender) may also influence the incidence of reward-scrounging. Thus, the relationship between the reward's design and reward-scrounging may also be an avenue for future research.

Finally, our data and our study design do not allow for a distinction between customers who accept an unnecessary reward on purpose and customers who accept such an award because of their unawareness of their own preferences. Alternative reasons may be the result of different drivers or the product of different economic behaviors in referral receivers. The same holds true for an in-depth analysis of the different referral modes that we analyze. Here, it would be interesting to experimentally examine what drives the decision making process regarding the two referral modes. Therefore, future studies should examine possible differences between samples and research designs that will enable psychological experiments.

Appendix A. Interaction of predictors with α coefficients

		Conversion Firm A		Conversion firm B		Conversion comp.	
		Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Local penetration firm A	Gender	0.022	0.013	0.000	0.026	−0.054	0.058
	Age	−0.001	0.012	0.024	0.026	−0.008	0.049
	Purchasing power	0.005	0.011	0.024	0.027	0.006	0.048
	Degree	−0.023	0.013	−0.002	0.025	−0.023	0.078
Exposure firm A	Gender	−0.001	0.013	−0.018	0.062	0.001	0.224
	Age	0.008	0.013	−0.139	0.063	0.008	0.217
	Purchasing power	−0.004	0.013	0.046	0.052	0.192	0.169
	Degree	0.000	0.011	0.107	0.037	0.223	0.161
Tie strength firm A	Gender	−0.004	0.013	−0.101	0.098	−0.763	1.746
	Age	−0.010	0.012	0.148	0.091	−0.452	0.260
	Purchasing power	0.002	0.012	−0.043	0.062	−0.252	0.105
	Degree	0.002	0.020	−0.401	0.211	−1.324	0.773
Advertising firm A	Gender	−0.035	0.021	−0.034	0.027	0.166	0.305
	Age	0.014	0.020	−0.007	0.025	−0.050	0.331
	Purchasing power	−0.019	0.021	0.035	0.025	−0.162	0.332
	Degree	0.014	0.019	0.000	0.024	−0.288	0.529
Local penetration firm B	Gender	0.047	0.018	0.035	0.018	−0.023	0.075
	Age	0.025	0.017	−0.014	0.019	−0.010	0.070
	Purchasing power	0.021	0.016	0.004	0.019	−0.035	0.057
	Degree	0.014	0.016	0.029	0.017	0.043	0.098

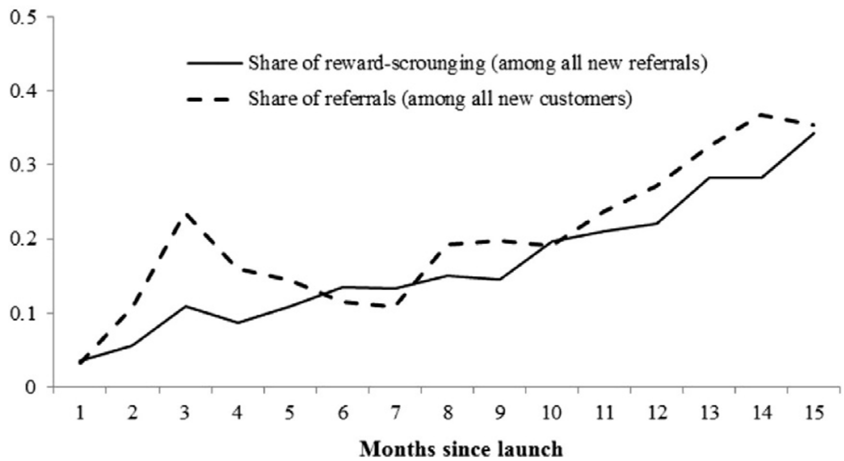
(continued on next page)

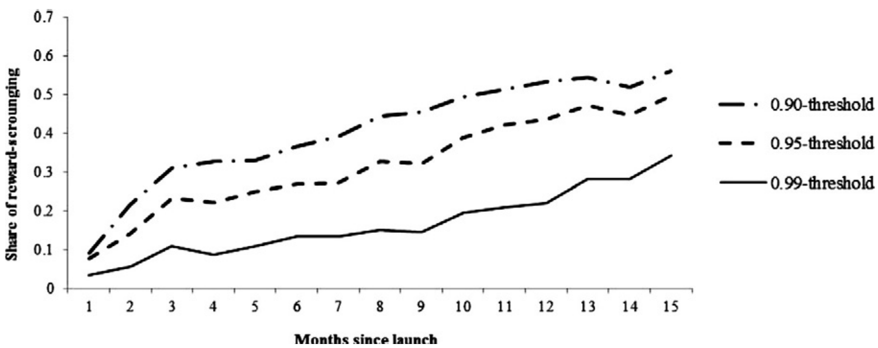
Appendix A *(continued)*

		Conversion Firm A		Conversion firm B		Conversion comp.	
		Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Exposure firm B	Gender	−0.026	0.025	−0.009	0.014	0.098	0.187
	Age	−0.057	0.023	−0.001	0.013	−0.069	0.208
	Purchasing power	−0.015	0.027	0.027	0.016	−0.275	0.345
	Degree	0.025	0.024	0.005	0.013	0.340	0.167
Tie strength firm B	Gender	−0.050	0.046	0.005	0.013	−0.189	2.039
	Age	0.062	0.054	−0.031	0.015	0.254	1.898
	Purchasing power	−0.074	0.044	−0.018	0.014	0.542	1.924
	Degree	−0.139	0.104	−0.010	0.017	−0.385	2.232
Advertising firm B	Gender	0.034	0.020	−0.028	0.024	−0.134	0.492
	Age	0.017	0.020	−0.022	0.023	−0.162	0.492
	Purchasing power	0.000	0.020	0.021	0.023	0.116	0.427
	Degree	−0.025	0.021	0.022	0.021	−0.290	0.812

All variables other than the intercept are standardized to be of mean 0 and variance 1; $N = 128{,}971$; $T = 15$.

Appendix B. Share of reward-scrounging dependent on chosen threshold





Note: Elasticity < 0.001 for all thresholds. Share of reward-scrounging refers to all new referrals.

Appendix C. Operationalization of reward-scrounging drivers

Variable	Operationalization
Network degree	Social network degree of referral sender
Homophily	Similarity of individuals based on sharing the same gender, the same age (±5 years), and the same network degree (±10 ties); 0 = no; 1 = yes, weighted by one third
Tie strength	Airtime of a dyad divided by the total airtime of a customer
Usage	Average revenue per month of referral sender (in Euro)
Advertising campaign	Advertising budget in conversion month that is at least twice as high as in the previous month (0/1)
Promotion campaign	Higher initial airtime for referral receiver in conversion month (0/1)
Time	Number of months between market launch and time of referral
Referral mode	Formal referral mode; 0 = receiver-stated; 1 = sender-stated
Multiple referrals	Number of referrals that the referral sender has sent out
Age	Referral sender's age in years
Gender	Referral sender's gender (1 = female)

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