A Lie Never Lives to be Old: The Effects of Fake Social Information on Consumer Decision-Making in Crowdfunding

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Complete Research

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Abstract

The growing success of social media led to a strong presence of social information such as customer product reviews and product ratings in electronic markets. While this information helps consumers to better assess the quality of goods before purchase, its impact on consumer decision-making also incentivizes sellers to game the system by creating fake data in favor of specific goods in order to deliberately mislead consumers. As a consequence, consumers could make suboptimal choices or could choose to disregard social information altogether. In this exploratory study, we assess the effects of non-genuine social information has on the consumer’s decision-making in the context of reward-based crowdfunding. Specifically, we capture unnatural peaks in the number of Facebook Likes that a specific crowdfunding campaign receives on the platforms Kickstarter and Indiegogo and observe subsequent campaign performance. Our results show that fake Facebook Likes have a very short-term positive effect on the number of backers participating in the respective crowdfunding campaign. However, this peak in participation is then followed by a period in which participation is lower than prior to the existence of the non-genuine social information. We further discuss circumstances that foster this artificial manipulation of quality signals.

Keywords: Fake Social Information, Perceived Quality, Signaling, Crowdfunding, Facebook Likes

1 Introduction

The growing success of social media has led to a strong presence of social information in electronic markets. This social information has become a vital quality signal for consumers to use for decision-support, as online transactions restrict the consumer’s ability to assess a product’s quality due to the lack of direct interaction with product and seller. Specifically, qualitative social information such as customer product reviews as well as quantitative social information such as product ratings and download rankings have been shown to affect consumers’ decisions when making online purchases (e.g., Chevalier and Mayzlin, 2006; Duan et al., 2008), helping them to overcome the information asymmetry for products whose quality is difficult to ascertain before purchase (Akerlof, 1970).

An extremely widespread method to reflect consumer opinions in a quantitative manner is the use of social media buttons such as the Facebook Like button, which is present on about 30% of the most popular websites worldwide (Built With, 2014). When placed on a website, the button shows a counter
reflecting the number of Facebook users who have previously “liked” this specific webpage or have shared the link to it with their peers (Facebook Inc., 2014). For subsequent visitors to the webpage, the button thus becomes a quality signal with a high number of Facebook Likes reflecting that the content or the offered product is of high quality, interesting or worth sharing for other reasons. However, unlike quantitative social information that is multifaceted and contains lots of information that can be considered by the consumer e.g. style and valence, social media buttons generally contain little information on a one-dimensional scale and most often no information about who contributed to the total count and why. Despite this limited information content, prior research has shown that quantitative social information can have a substantial influence on the decision-making of consumers (e.g., Duan et al., 2009; Tucker and Zhang, 2011). These studies, however, were focused on ordinal rankings that reflect actual popularity of a specific product among consumers. In contrast, the counter on the Facebook Like button only captures preferences and does not necessarily reflect actual behavior such as how many consumers have bought a product or downloaded specific software. The Facebook Like button thus remains a relatively subjective measure of popularity. Nevertheless, this social information can potentially be of high relevance for consumers in situations in which assessing the quality of specific products is especially difficult (e.g., Schöndienst et al., 2012; Thies et al., 2014). This is particularly true for products and services financed through reward-based crowdfunding platforms such as Kickstarter and Indiegogo. Here, the so-called backers invest in campaigns that appeal to them in the hope to receive adequate tangible rewards for their investment, even though they are not guaranteed legally (Mollick, 2014). In addition to the risk of not receiving a reward at all, the quality of the reward remains unpredictable at the time the investment decision has to be made, because the rewards have not been created yet. Consequently, the utility of the rewards can only be ascertained when receiving them after the campaign has ended, thus increasing the relevance of quality signals such as the Facebook Like button in this setting.

Both Kickstarter and Indiegogo display the Facebook Like button prominently in the description of every crowdfunding campaign in order to facilitate a viral dissemination of the campaign through social media. This growing presence of social media and social information, however, also incentivizes individuals and organizations to game the system by creating fake data in favor of specific campaigns in order to deliberately mislead consumers (Facebook Inc., 2015a). As a consequence, backers on crowdfunding platforms could make suboptimal choices based on the biased information or could choose to disregard or underweight otherwise helpful social information by mistrusting this content all together (Mayzlin et al., 2012). Faking social information has thus become a preeminent threat to the credibility and trustworthiness of this type of user-generated content (Luca and Zervas, 2013).

While there is a growing stream of research in the area of computer science focused on uncovering non-genuine qualitative social information (e.g., Jindal et al., 2010; Li et al., 2011), little research has been devoted to identifying fake quantitative social information and especially to measuring its impact on consumer decision-making. Against this background, we focus our research on the effects non-genuine Facebook Likes have on the decision-making of prospective backers on the crowdfunding platforms Kickstarter and Indiegogo. Furthermore, by examining the characteristics of campaigns that receive fake Facebook Likes during the campaign life cycle, we uncover conditions under which there is an increased probability for backers to be confronted with fake Likes. The objective of our exploratory study is to address the discussed research gaps guided by the following research questions:

**RQ 1:** How does fake social information in the form of Facebook Likes affect the decision-making of backers on crowdfunding platforms?

**RQ 2:** What circumstances make crowdfunding campaigns more prone to receiving fake Facebook Likes?

To answer our first research question, we employ a self-developed algorithm to identify fake social information and estimate a fixed effect negative binominal regression to uncover the effects on the decision-making. We continue by using a panel probit estimation to model the probability of the occurrence of fake Likes depending on several environmental factors such as market competition.
2 Theoretical Background and Prior Research

2.1 Information Asymmetry and Signaling

The quality of a product or service is often difficult to ascertain in electronic markets as the lack of physical contact prevents consumers from using their senses such as touch, smell, and taste when evaluating quality. As a result, the consumer lacks information about the product’s or service’s true quality until after delivery. This uncertainty associated with online purchases can lead to an information asymmetry between buyer and seller, as the seller alone controls the flow of information towards the buyer and is thus able to overstate quality or withhold information (Mavlanova et al., 2012). This information distortion may then lead to an adverse selection problem where consumers, when faced with a decision between two different goods, make buying decisions based on price rather than quality (Akerlof, 1970).

Even though physical search costs on the internet are negligible, search costs may thus arise due to the difficulty of evaluating the true quality of goods. Consequently, as consumers become increasingly uncertain about a product’s true quality, they may rely more on alternative information sources that are available. This phenomenon has been, for example, confirmed for brand equity (Krishnan and Hartline, 2001). However, alternative information might only be available for established products and newness of a product or firm can thus make it harder for consumers to gather information on its true quality. This is particularly true for the rewards promised as a return for the investment in crowdfunding campaigns, as these rewards often do not even exist at the time the investment decision has to be made. Consequently, in these situations, in which the agent (the seller) possesses information that the principal (the buyer or backer) does not have or in which the principal is unable to evaluate the quality, the principal can draw inferences from credible signals send by the agent (Biswas and Biswas, 2004). A product warranty, for example, does not change intrinsic attributes of a product but creates trust, which in turn may reduce uncertainty in buying situations (Yen, 2006). Signaling theory is concerned with understanding why certain signals such as a product warranty might be reliable and could thus be relevant to the consumer in buying situations (Spence, 1973). Prior research has shown that businesses are able to signal product quality through, for example, advertising and pricing (Kirmani and Rao, 2000). These signals may, however, become even more credible to the consumers when sent by other consumers instead of businesses. The internet allows consumers to exchange opinions and recommendations on a large scale through social information such as online customer product reviews.

2.2 Fake Social Information as a Signal of Product and Service Quality

The question whether social information can have an effect on the consumers’ quality perceptions and subsequent buying decisions has attracted scholars from a variety of research areas such as marketing, economics, and information systems. Prior research has shown that both qualitative as well as quantitative social information does in fact have an influence on consumer decision-making in many buying situations. For example, word-of-mouth has been shown to have a positive effect on the box office revenues of movies (Liu, 2006) and positive customer product reviews lead to increases in book sales on Amazon (Chevalier and Mayzlin, 2006). On the other hand, research on the effects of quantitative social information such as download rankings and product ratings has yielded ambiguous results. For example, Duan et al. (2009) demonstrate that, when choosing software products, consumers are strongly affected by download rankings, while product ratings only have an effect on the user’s adoption of niche products and not for the adoption of the popular one. The difference in these findings can be explained with the structural differences between qualitative and quantitative social information and between rankings and ratings. Customer product reviews, for example, allow consumers to express their opinions in respect to a product or service in a vivid description and thus contain considerable more information than a one-dimensional scale such as a product rating. Furthermore, compared to popularity rankings such as software download rankings, product ratings do not necessarily reflect actual behavior such as how many consumers have bought a product. The same is true for the counter
on the Facebook Like button that captures preferences and does not necessarily reflect actual behavior. Nevertheless, prior research has shown that consumers perceive Facebook Likes as a quality signal and that they associate more Likes with a superior product or service quality (Schöndienst et al., 2012).

Despite the high relevance of social information as a quality signal for consumers, relatively little prior research exists on biases that may appear in this context. For example, Dellarocas et al. (2010) have found that consumers are more likely to review less available and less successful products in the market but, at the same time, are also more likely to contribute reviews for products that already received a high number of reviews. Furthermore, it has been shown that reviews posted early in a product’s lifetime tend to be positively biased (Li and Hitt, 2008). A more substantial and preeminent threat to the credibility and trustworthiness of social information as a quality signal, however, is the possibility of creating fake data (Luca and Zervas, 2013). Even though some governments have reacted to the growing trend of surreptitious advertising through, for example, customer product reviews and these kinds of endorsements and testimonials now have to be classified as such (e.g., Federal Trade Commission, 2009), faking this data is still a growing trend. Consequently, it remains challenging for providers of online services to identify social information that does not reflect genuine consumer opinions or behavior by, for instance, increasing the cost of posting fake content (Mayzlin et al., 2012). Popular websites such as Yelp.com use algorithms to identify and mark specific reviews as fraudulent (cf., Jindal et al., 2010; Li et al., 2011). On Yelp, fraudulent reviews account for 16% of all reviews and tend to be particularly extreme (either favorable or unfavorable) (Luca and Zervas, 2013). While consumers might be able to identify fake qualitative content due to its extreme nature and exaggerations contained therein, purely quantitative non-genuine content such as a rating is generally more difficult to identify by service providers and especially by consumers. This is a particular challenge in the context of Facebook Likes as a quality signal, as it remains impenetrable to the consumer whether the Likes are a genuine signal sent by other consumers or a non-genuine signal sent by sellers.

Quality signals can only be credible if a seller offering a low quality has higher costs acquiring them compared to a seller offering a high quality (Kirmani and Rao, 2000; Connelly et al., 2011). It has been shown that content that creates high-arousal positive emotions and is surprising, interesting, or practically useful is shared often among online users (Berger and Milkman, 2012). As these are all characteristics of high quality crowdfunding campaigns, it can be assumed that these campaigns receive more Facebook Likes without any extra costs. In turn, this would mean that low quality campaigns would need to acquire additional Likes in different ways. Acquiring fake Likes is, for instance, possible by creating dedicated fake Facebook accounts that can then be used to “like” specific webpages or by turning to crowdsourcing marketplaces such as Amazon Mechanical Turk where 1,000 Facebook Likes can be acquired for as little as $15 (Arthur, 2013).

While these low costs of acquiring Facebook Likes should depreciate their value as a quality signal, we argue that this might not necessarily be the case. As long as Facebook is able to control the spread of fake Likes and thus the vast majority of Likes remains genuine, consumers will often be unable to quickly identify fake Facebook Likes as such (Facebook Inc., 2015b; Gara, 2013). Furthermore, with rising search costs and scarcity of information, the relative contribution or importance of the remaining information may increase. Therefore, social information such as Facebook Likes that contains relatively small amounts of information may be a credible signal in high search-cost situations such as crowdfunding platforms. Thus, given that social information has an effect on the consumer’s buying decisions in many situations, as shown in prior research, we expect fake Facebook Likes to have a positive influence on the prospective backer’s perception of a campaign’s quality, leading to an increase in the number of backers in the following period.

**Proposition 1:** An artificially created positive shock in the number of Facebook Likes that a crowdfunding campaign receives will lead to an increase in the number of backers pledging for the campaign in the following period.
While we expect fake Facebook Likes to positively affect the number of backers contributing to the campaign in the following period, this effect might be very short-lived. First, prior research has shown that an increase in genuine Facebook Likes has its biggest effect on contribution behavior of backers within a day (Thies et al., 2014). Second, fake Facebook Likes are unlikely to attract any additional prospective backers to the campaign webpage as the fake Facebook accounts created for the purpose of adding non-genuine Likes will not have any connections to real “friends”. Consequently, these fake Likes will not disseminate through Facebook’s social network and this information will thus not be seen by any real Facebook users. Hence, fake Likes cannot attract any additional prospective backers to the campaign webpage. The only users potentially affected by the increase in the number of Likes are therefore those who see the Facebook Like button directly on the webpage and who visit the campaign webpage anyway for other reasons. Prospective backers who notice the high or increased number of Facebook Likes would thus only expedite their pending investment decision, which they would otherwise have taken later on once other performance indicators (e.g. pledged amount, number of backers, number of tweets, number of updates) reflect that the campaign is of high quality. This would mean that a declining growth would follow the positive peak in the number of additional backers. We thus propose that:

**Proposition 2**: Any positive effect of fake Facebook Likes on the number of backers will vanish quickly and will be followed by a lower than average number of additional backers over time.

### 2.3 Campaign and Platform Characteristics in Reward-Based Crowdfunding

Crowdfunding is a subset of crowdsourcing that enables the creators of campaigns to collect relatively small financial contributions from a large number of individuals through an open call on the internet (Schwienbacher and Larralde, 2012). It thus creates a large, relatively undefined network of project stakeholders and consequently decreases the importance of other investors such as venture capitalists.

Crowdfunding also offers a variety of incentives for backers to “pledge” for a specific campaign. These incentives mainly depend on the return the backers can expect from their contributions, which range from donations to company equity (Ahlers et al., 2012). On Kickstarter and Indiegogo, the most common and salient type of return is a so-called “reward” that often allows backers to be among the first customers to sample the product or service financed through the campaign. In this study, we focus on this so-called reward-based crowdfunding, as it is by far the most widespread concept of crowdfunding today (Kartaszewicz-Grell et al., 2013).

Compared to other types of web services, reward-based crowdfunding is special as it allows us to observe the effects fraudulent social information has on the decision-making of backers over the complete campaign life cycle and the high uncertainty connected to the investments made by backers makes it the ideal vehicle to test the effects of fake Facebook Likes. This high uncertainty results from the lack of a legal obligation to actually deliver the rewards to the backers and the fact that the quality of the rewards remains highly unpredictable at the time the investment decision has to be made.

The dynamics of crowdfunding are thus different from those in a traditional e-commerce setting between a seller and a buyer. Backers can be less certain that they will actually receive a return on their investment and have less information about the object they are investing in compared to a regular buying situation, in which the product or service already exists. The primary source of information for a potential backer is the campaign description the creator has published. Even though this content allows prospective backers to develop an attitude towards the campaign and the comprised rewards, this attitude is potentially biased due to the fact that it stems from a single source of information (Burgh et al., 2013). We therefore argue that other evidence for the trustworthiness and quality of a campaign such as the Facebook Likes it receives becomes increasingly important for the potential backer’s evaluation.

The question remains, what characteristics of crowdfunding platforms and campaigns will make it most likely for backers to be confronted with fake Facebook Likes? For this study, we deliberately chose two quite different crowdfunding platforms operating in the same market, namely Kickstarter
and Indiegogo, as this allows us to better assess effects of their unique characteristics on the occurrence of non-genuine social information. Unlike Indiegogo, Kickstarter applied rigorous input control mechanisms during almost the complete observation period (Kickstarter, 2014), meaning that Kickstarter staff verified the quality and likelihood of success of every campaign manually before it could be published on the platform (Cardinal, 2001; Benlian et al., 2015). Assuming that this control mechanism increased the average campaign quality on Kickstarter, these campaigns should receive more genuine Facebook Likes without any extra costs compared to campaigns on Indiegogo (Benlian and Hess, 2011). Furthermore, due to the input control applied by Kickstarter, being allowed to publish a campaign on the platform becomes a quality signal in itself, decreasing the importance of other signals. We therefore expect the less regulated platform Indiegogo to be more prone to artificial manipulations in respect to fake Facebook Likes.

**Proposition 3**: Controlled markets decrease the likelihood of an artificial manipulation of quality signals.

For the same reason, we expect to see a negative correlation between the quality of individual campaigns and the number of fake Likes they receive.

**Proposition 4**: Campaign quality decreases the likelihood of an artificial manipulation of quality signals.

Crowdfunding campaigns on Kickstarter and Indiegogo can most often be characterized as innovative and quite unique in respect to the project ideas. As a result, backers will rarely have to choose between two similar campaigns running at the same time. Nevertheless, each campaign has to compete with all other campaigns running at the same time for the attention of the prospective backers browsing the crowdfunding campaign. This is particularly true within the distinct categories (e.g., technology or design) that are used on the platforms to sort and rank campaigns. Consequently, crowded categories or those hosting particularly successful campaigns will make it more difficult for the individual campaigns to be noticed. Prior research has shown that, as the intensity of competition increases, market participants invest less in satisfying market rules (Branco and Villas-Boas, 2012; Luca and Zervas, 2013). As truthfulness and honesty are among the rules that campaign creators have to comply with on Kickstarter and Indiegogo, an increased competition should then lead to an increase in the average number of fake Likes per campaign.

**Proposition 5**: Competition increases the likelihood of an artificial manipulation of quality signals.

3 Research Methodology

In most cases, creating fake Facebook Likes will be a decision taken and executed by the creators of a specific crowdfunding campaign in the hope to send a quality signal to prospective backers. The shock in the number of Facebook Likes can thus be assumed to be endogenous to the campaign creators but exogenous to the platform providers and the backers (Claussen et al., 2013). In order to explore the effects of non-genuine Facebook Likes, we employ three different methods. First, we provide descriptive evidence on the distribution of fraudulent behavior on the focal platforms. Second, we investigate the effect of the artificial manipulation using a panel fixed effect negative binominal regression model, treating the purchase of fake Likes as an endogenous shock (Cameron and Trivedi, 2013). Third, we use a probit model with the occurrence of fake Facebook Likes as the binary dependent variable. We are therefore able to assess the influence of the different characteristics of campaigns on the likelihood that manipulation occurs (Finney, 1971; Cameron and Trivedi, 2005).

3.1 Dataset and Identification of Campaigns with Fake Likes

Our campaign-level data was collected from Kickstarter and Indiegogo, which are the leading and most prominent reward-based crowdfunding platforms today. Since Kickstarter’s launch in 2009, over $1.6 billion have been pledged by more than 8 million individuals, funding more than 80,000 projects
(Kickstarter, 2015). Indiegogo, on the other hand, does not make their statistics similarly public, but there are some prominent examples such as the Ubuntu Edge Smartphone that raised over $12 Million in 2013 (Nunnelly, 2013). Our data covers the period from November 15th 2013 to August 18th 2014, resulting in 1.85 million observations and over 80,000 campaigns. Data on every campaign available was gathered automatically with a self-developed web crawler to retrieve time-series data on all campaigns in a daily routine.

Campaigns involved in the artificial manipulation of quality signals were identified as such, when unnatural peaks in Facebook Likes occurred on a single day. Even though natural peaks in Facebook Likes are to be expected when a campaign receives major attention in other channels, such as blogs or news sites, these peaks are then followed by an increased and then gradually declining number of daily Likes over time. Campaigns were therefore identified using a self-programmed algorithm, marking campaigns that received more than a threefold standard deviation of Facebook Likes in a single day (Aggarwal, 2013). Furthermore, the number of additional Likes had to exceed 500, as the former rule is impractical for small values and vendors of Facebook Likes commonly sell them in a quantities of at least 500 (Steuer, 2013). The same procedure was applied to ensure that a significant drop in the additional number of Facebook Likes occurs. Meaning that on the following day, a threefold standard deviation decline must be present. Using a threefold standard deviation is a conservative approach to identify peaks, as in a normal distribution 99.7 % of all observations are inside this interval. Applying the filtering mechanism still resulted in 874 projects for Kickstarter and 1,289 for Indiegogo that were identified as being involved in fraudulent actions in respect to Facebook Likes.

3.2 Model

Panel Poisson models are commonly used when the dependent variable is a count. We used negative binominal regression models in our analysis, because the dependent variable is overdispersed, meaning its variance is bigger than its mean (Cameron and Trivedi, 2013). We employ a conditional fixed-effects specification (Hausman and Taylor, 1981) to control for unobserved heterogeneity by estimating effects using only within project variation. Therefore, these models drop campaigns with no day-to-day variation in additional backers. Our conclusions to be discussed are generally robust to random effects models, but the performed Hausman specification test suggested that fixed-effects modeling is preferred (Hausman and Taylor, 1981). Our dependent variable is the additional number of backers a campaign acquires each day and which measures the adoption rate during the life cycle of a campaign. Resulting in the following model specification for our baseline regression:

\[ y_{it} = \alpha_i + \beta x_{it} + \gamma z_i \]

where \( y_{it} \) is the dependent variable describing the additional backers on each day. The individual-effects negative binominal model assumes that \( y_{it} \) takes non-negative integer values and is overdispersed. Our independent variable is represented by \( \beta x_{it} \). Here, \( \alpha_i \) depicts campaign specific fixed effects controlling for all time-invariant characteristics that might drive the number of additional backers on each day. Again, the time-invariant, campaign-specific heterogeneity is absorbed by the campaign’s fixed-effects. However, as we are using a negative binominal model, we were able to include some time-invariant variables by using a set of panel dummies (Allison and Waterman, 2002).

Probit models are well established and used for binary outcomes in regression analysis. Probit models specify the probability of an outcome as a function of one or more regressors. In our case, we model the probability of the occurrence of fake Likes dependent on several environmental factors (Cameron and Trivedi, 2005). Our model is then formalized as follows:

\[ p_i = PR[y_i = 1|x_i] = \Phi(\beta_1 + \beta_2 x_i) \]

Here \( y_i \) is the occurrence of fake Facebook Likes depending on campaign characteristics \( x_i \).
3.3 Variables

We use the number of additional backers on each day as our dependent variable for the following reasons. First, our intention was to examine the impact fraudulent behavior has on the individual decision to support a campaign and not the amount of funding a backer gives. Therefore, the number of backers instead of additional pledge amount is preferred. Second, single and extremely high donations, possibly by the project creators themselves, might also severely distort the results.

To control for the possibility that additional backers decided to support a campaign because of a crucial update in the campaign description, we included a simple count accumulating each update on a given day. Furthermore, we included a factor variable for each category as a control variable. Summary statistics for our final dataset and all relevant variables are depicted in Table 1. All Summary statistics, except the delta values, show the value of each variable at the end of the campaign life cycle.

Our dependent variable for the probit regression is binary and marks all projects that have purchased Facebook Likes with 1. In order to assess the proposed influence of campaign quality and market competition we use several proxy variables in our regression. One key element here, is if the campaign includes a video (Mollick, 2014). Further indicators of quality are the number of updates, the social network of the creator, the duration of the campaign (Kuppuswamy and Bayus, 2014; Agrawal et al., 2011), and creator experience (Zhang, 2006). In order to assess market competition, we apply two different measures. First, we use the Hirschman-Herfindahl index from strategic management research to measure the level of concentration in project categories each period (Hirschman, 1964; Hansen and Haas, 2001). Second, we measure the daily crowdedness of each category by dividing the number of current campaigns within a category by the average number of campaigns per category (Chellappa et al., 2010).

3.4 Robustness Checks

To check for the robustness of our results, we ran our regressions with a more narrow definition of unnatural peaks, by looking at projects that deviated from their usual growth rate by a fifth fold standard deviation. Furthermore, we also changed our primary dependent variable to the natural logarithm of the daily income of the project as backers differ in terms of their financial contribution to the project. All robustness checks showed the same result patterns and confirmed our model and choice of variables. As a robustness check for our probit regression, we used an OLS estimator. This analysis also confirmed the patterns of our results.

4 Results

We now present the results of our analysis, starting with the descriptive evidence, followed by the results for the fixed-effects negative binominal regression, and the probit regression. Table 1 provides the summary statistics on a campaign level for all available campaigns and a subset for the manipulated campaigns. We present the results of our main model in Table 2, which provides evidence for the effects of manipulated social information on the backing behavior of the crowdfunding community. We conclude with our probit model in Table 3 to show, what factors of a crowdfunding campaign influence the occurrence of fake Facebook Likes.

4.1 Descriptive Evidence

Before we focus on answering our research questions, we first study the descriptive statistics for all campaigns and for those affected by the artificial manipulation of Facebook Likes on both platforms that are shown in Table 1. Campaigns receive an average of $7,824 on Kickstarter, while on Indiegogo only about $3,200 are accumulated on average. A campaign on Kickstarter received on average 350 Facebook Likes and 326 on Indiegogo. The number of Facebook friends a creator has is only available for Kickstarter, while team size is only reported on Indiegogo.
Table 1. Summary Statistics for the complete dataset and for campaigns that received fake Likes

<table>
<thead>
<tr>
<th>Complete dataset</th>
<th>Kickstarter (N= 46,228)</th>
<th>Indiegogo (N=35,370)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Fake Likes (Dummy)</td>
<td>0.019</td>
<td>0.136</td>
</tr>
<tr>
<td>Facebook Likes</td>
<td>350.94</td>
<td>5,040.46</td>
</tr>
<tr>
<td>Backers</td>
<td>97.66</td>
<td>717.08</td>
</tr>
<tr>
<td>Accum. funding</td>
<td>7,824.19</td>
<td>74,035.03</td>
</tr>
<tr>
<td>Funding goal</td>
<td>45,011.57</td>
<td>1,283,560</td>
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<tr>
<td>Campaign duration</td>
<td>33.25</td>
<td>10.76</td>
</tr>
<tr>
<td>No. of rewards</td>
<td>8.20</td>
<td>6.02</td>
</tr>
<tr>
<td>Video</td>
<td>0.72</td>
<td>0.45</td>
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<tr>
<td>Updates</td>
<td>2.42</td>
<td>4.50</td>
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<tr>
<td>Campaigns backed</td>
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<td>14.11</td>
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<tr>
<td>Campaigns created</td>
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<td>1.86</td>
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<td>Facebook friends</td>
<td>651</td>
<td>777</td>
</tr>
<tr>
<td>Team size</td>
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<td>.</td>
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<tr>
<td>Concentration</td>
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<td>0.048</td>
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<tr>
<td>Crowdedness</td>
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<td>0.49</td>
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</table>

<table>
<thead>
<tr>
<th>Fake Likes</th>
<th>Kickstarter (N=874)</th>
<th>Indiegogo (N=1,287)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
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<tr>
<td>Facebook Likes</td>
<td>4,038.38</td>
<td>11,416.74</td>
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<tr>
<td>Δ Facebook Likes</td>
<td>151.29</td>
<td>1,884.58</td>
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<tr>
<td>Backers</td>
<td>813.80</td>
<td>1,678.78</td>
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<tr>
<td>Δ Backers</td>
<td>30.49</td>
<td>149.16</td>
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<tr>
<td>Accum. funding</td>
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<td>233,081.2</td>
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<td>Funding goal</td>
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</tbody>
</table>

Figure 1 depicts the distribution of fraudulent behavior with respect to the campaign category. We immediately recognize the higher standard deviation for Indiegogo, where over 9% of campaigns in the category “Technology” showed unnatural peaks in the growth of Facebook Likes. However, it can be seen that, despite the higher standard deviation, the categories in which campaigns are most and least prone to receive fake Likes are distributed rather similarly between both platforms.

![Percentage of campaigns in the distinct categories on Indiegogo and Kickstarter that received non-genuine Facebook Likes during the campaign life cycle](image-url)
As we are using a panel dataset, we are able to identify the exact date a campaign received the non-genuine Facebook Likes. Figure 2 shows the growth of Facebook Likes for two separate campaigns from our dataset over the campaign life cycle and serves as an illustrative example for the distinct peak that can be observed when non-genuine Facebook Likes are acquired compared to a natural growth. We further use our data to plot the date of the acquisition against the accumulated funding the campaign eventually received by the end of the campaign life cycle (Figure 3). Each dot represents the exact point in time when the unnatural peak occurred. On the y-axis, we depicted the fraction of the total amount of the accumulated funding a campaign raised. We can see that the majority of creators try to increase the odds of success by making use of the artificial manipulation of Likes early in the campaign’s life cycle, represented by the dense cluster in the lower left corner. Drawing from this representation, we can also see that most campaigns are above the reference line, indicating that their action hurt their funding progress. Many campaigns were even unable to attract any additional funding after the manipulation of Facebook Likes, as represented by the dots on the top end. Interestingly, we do not see any apparent differences between Kickstarter and Indiegogo in this graph.

![Figure 2. Example of genuine and non-genuine peaks in Facebook Likes](image)

![Figure 3. Timing of unnatural peaks with respect to funding and life cycle](image)

### 4.2 Effects of Fake Facebook Likes on the Decision-Making of Backers

We now turn to our econometric evidence for the effect fake social information in the form of Facebook Likes has on the decision-making of prospective backers on Kickstarter and Indiegogo. We ran a total of four models for our econometric results as depicted in Table 2. The first two used our data of Kickstarter, while the latter two models describe the effects on Indiegogo. Specification 1-1 and 2-1 include a before/after dummy for the purchase of Fake Likes. In order to model the dynamic effects and to rule out other rival explanations, we create a set of ten dummies for the 5 days pre and post the artificial manipulation in the specifications 1-2 and 2-2. Observations in Model 1-2 and 2-2 are thus restricted to be within a 10 day time period from the purchase of Fake Likes.

The negative and significant coefficient Fake Likes Dummy in model 1-1 and 2-1 clearly indicates a negative effect of non-genuine Facebook Likes for both platforms. Consequently, campaign creators who try to increase the odds of success for their campaigns by acquiring fake Likes do in fact achieve the opposite. However, when looking at the dynamic effects in model 1-2 and 2-2, we can observe a positive and significant coefficient for the first day following the artificial manipulation of the Likes as it was expected (Proposition 1). Furthermore, we also see the predicted subsequent drop in funding...
activities represented by the consecutively negative coefficient after T+1, which can be attributed to the fact that backers who planned to participate anyway expedited their investment based on the non-genuine social information (Proposition 2). Even though these effects exist on both platforms in the same direction, we see slightly higher coefficients for Kickstarter. We also notice preceding negative significant coefficients on Indiegogo for T-4 and T-5. A possible explanation might be that, as creators notice a decline in the number of backers, they choose to acquire fake Likes to counteract this decline.

<table>
<thead>
<tr>
<th></th>
<th>Kickstarter</th>
<th>Kickstarter</th>
<th>Indiegogo</th>
<th>Indiegogo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Backers</td>
<td>1-1</td>
<td>1-2</td>
<td>2-1</td>
<td>2-2</td>
</tr>
<tr>
<td>Independent variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Updates</td>
<td>-0.0071*** (-4.00)</td>
<td>0.005 (1.04)</td>
<td>0.0035*** (3.21)</td>
<td>0.023 *** (8.98)</td>
</tr>
<tr>
<td>Category dummies</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Fake Likes (Dummy)</td>
<td>-0.14*** (-7.42)</td>
<td>-0.24*** (-14.38)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-5</td>
<td>0 (.)</td>
<td></td>
<td></td>
<td>0 (.)</td>
</tr>
<tr>
<td>T-4</td>
<td>-0.096 (-1.45)</td>
<td>-0.19*** (-3.28)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-3</td>
<td>-0.1 (-1.56)</td>
<td>-0.14*** (-2.50)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-2</td>
<td>-0.036 (-0.57)</td>
<td>-0.021 (-0.39)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-1</td>
<td>0.022 (0.37)</td>
<td>0.0094 (0.18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T+1</td>
<td>1.2*** (22.61)</td>
<td>0.93*** (19.62)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T+2</td>
<td>-0.2*** (-3.58)</td>
<td>-0.1** (-1.96)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T+3</td>
<td>-0.28** (-4.94)</td>
<td>-0.2*** (-3.76)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T+4</td>
<td>-0.49*** (-8.58)</td>
<td>-0.32*** (-5.84)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T+5</td>
<td>-0.53** (-9.02)</td>
<td>-0.38** (-6.89)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>_cons</td>
<td>-0.087 (-1.78)</td>
<td>0.14 (1.30)</td>
<td>-0.51*** (-10.14)</td>
<td>-0.45*** (-4.28)</td>
</tr>
<tr>
<td>BIC</td>
<td>150,867</td>
<td>34,816</td>
<td>151,696</td>
<td>37,555</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-75,348</td>
<td>-17,299</td>
<td>-75,710</td>
<td>-18,619</td>
</tr>
<tr>
<td>Wald Chi²</td>
<td>164</td>
<td>4,417</td>
<td>5,37</td>
<td>2,004</td>
</tr>
<tr>
<td>Campaigns</td>
<td>874</td>
<td>873</td>
<td>1,287</td>
<td>1,268</td>
</tr>
<tr>
<td>Observations</td>
<td>23,329</td>
<td>6,107</td>
<td>41,357</td>
<td>10,909</td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001

Table 2. Results from Fixed Effects Negative Binominal Regression

4.3 Effects of Platform and Campaign Characteristics on the Likelihood of Fake Facebook Likes

While the effects of the fake social information on the decision-making of backers showed several similarities between both platforms, further increasing the validity of our findings, we also see a number of differences between Kickstarter and Indiegogo in respect to the circumstances under which campaigns with fake Likes are most prevalent. First, our algorithm identified unnatural peaks in 3.6 % of the campaigns on Indiegogo, while only 1.9 % of the campaign creators on Kickstarter used non-genuine Likes to promote their campaign. This difference was to be expected due to the platforms’ different approaches to governance and its effect on the average campaign quality, as discussed in Proposition 3. This means that on Kickstarter, many of the campaigns that would be prone to artificial manipulation of quality signals are filtered out before they are even allowed onto the platform and the remaining campaigns will generally be shared more on social media due to the increased quality.

In order to test whether any correlation exists between the characteristics of individual campaigns and the likelihood of any artificial manipulation of quality signals, we used a probit model with the occurrence of fake Facebook Likes as the binary dependent variable (Table 3). Though this does not allow us to interpret the coefficients directly, we are able to interpret whether the respective characteristics
have a positive or negative effect on the likelihood of fake Facebook Likes. To assess the role of individual campaign quality, we mainly focused on the role of preparedness as a signal of quality to the prospective backers (Chen et al., 2009; Mollick, 2014). We thus selected variables from our dataset that reflect how well prepared and how involved in the community the creators of the campaigns were.

One of the key elements of every crowdfunding campaign on both platforms is the campaign video. A high quality video would, for example, make it more likely for potential backers to share the campaign via Facebook and could thus make it less attractive for the creators to acquire additional fake Facebook Likes. Surprisingly and in contrast to Proposition 4, we see that if a video exists, the artificial manipulation of social information becomes more likely. The same is true for a number of other variables such as the number of updates a creator provides during the campaign life cycle (see Table 3).

Finally, we also proposed that, as the intensity of competition increases, creators will be less interested in following the market rules and more likely to acquire fake Likes. We thus measured the dynamic market crowdedness and concentration (Herfindahl–Hirschman Index) for every category on both platforms in order to determine the intensity of competition on each day. The results in Table 3 suggest that, on Kickstarter, an increased competition does in fact increase the likelihood of artificial manipulations of quality signals in the respective category, while there is no similar effect on Indiegogo.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kickstarter</th>
<th>Indiegogo</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(funding goal)</td>
<td>0.2***</td>
<td>0.14***</td>
</tr>
<tr>
<td>ln(updated)</td>
<td>-0.24 (-0.97)</td>
<td>-0.24 (-0.97)</td>
</tr>
<tr>
<td>ln(Facebook friends)</td>
<td>0.18***</td>
<td>–</td>
</tr>
<tr>
<td>Team size</td>
<td>–</td>
<td>-0.006 (-0.71)</td>
</tr>
<tr>
<td>Concentration</td>
<td>1.2***</td>
<td>-0.088 (-0.25)</td>
</tr>
<tr>
<td>Crowdedness</td>
<td>0.12**</td>
<td>-0.0063 (-0.16)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-2.230</td>
<td>-2.243</td>
</tr>
<tr>
<td>Wald-Chi²</td>
<td>795</td>
<td>1123</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.2</td>
<td>0.22</td>
</tr>
<tr>
<td>Observations</td>
<td>30,159</td>
<td>20,152</td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses; A constant is estimated but not reported; p < 0.05, ** p < 0.01, *** p < 0.001

Table 3. Results from the Probit Regression

5 Discussion and Implications

After reviewing our descriptive and econometric evidence, we will now link these results to our initial research questions. First and foremost, our analysis clearly shows that non-genuine social information in the form of fake Facebook Likes does in fact influence the investment decisions of backers. The negative coefficient, however, shows that overall the manipulation slows down participation and the creators thus achieve the opposite of what was intended. An explanation for this might be that some of the very internet-savvy prospective backers notice a discrepancy between the number of Facebook Likes the campaign received and other performance indicators such as the number of backers and, as a result, reconsider investing in the respective campaign. Still, our econometric model showed that a short-term gain can be induced by acquiring fake Facebook Likes. However, as fake Likes will not disseminate through Facebook’s social network, this gain cannot be expected to stem from any additional visitors to the campaign website but will rather be caused by backers who expedite their invest-
ment decisions based on the observed peak. It is therefore not surprising that the positive peak is directly followed by a decelerated growth rate.

For our second research question, we present several factors that can increase the likelihood of manipulations. First, campaigns on Indiegogo are more prone to the artificial manipulation of quality signals. This might be due to the fact that Kickstarter enforced strong control mechanisms, while Indiegogo did not control or audit their campaign creators. Second, categories for creative campaigns such as art, crafts, dance, and comics are less likely to be affected by Fake Likes. This effect can possibly be attributed to the fact that these campaigns tend to be shared more via social media anyway (Thies et al., 2014; Berger and Milkman, 2012). Third, creators who invest more time and effort creating and managing their campaign are more prone to acquiring fake Likes. A possible explanation might be that, as they have invested more, they feel a stronger urge to make their campaign succeed, even if this means to game the system. Fourth, on Kickstarter we see that a stronger competition within categories also increases the likelihood of fake Likes. The fact that this correlation does not exist on Indiegogo suggests that, since the platform is less regulated, diversity will be higher, thus decreasing direct competition. Finally, we also provide evidence for the timing of the acquisition of fake Likes with respect to funding raised and campaign life cycle and see that the majority of creators acquire non-genuine Likes early in the campaign’s life cycle and many are unable to generate any additional funding afterwards.

To the best of our knowledge, this is one of the first studies focused on the effects of fake social information on consumer decision-making. We were able to show that, despite the low information content, quantitative social information can have a substantial effect on consumer decision-making. This shows that consumers consider Facebook Likes, genuine and non-genuine, as quality signals though they only reflect preferences and no actual consumer behavior. Our study thus contributes to social media research by advancing our understanding of the differential effects social information can have on consumers and by highlighting the role of artificial manipulations in this context.

Furthermore, we also see practical implications that should be considered. Creators should be aware that, even though social information can be a decisive factor for campaign success and an important quality signal, acquiring non-genuine Facebook Likes will not attract any additional backers. For platform providers, our results provide insights on both the extent of gaming as well as under what market conditions and campaign characteristics it is most prevalent. For example, we show that in a more controlled market, it might become less likely that creators use fake Likes to promote their campaigns.

6 Limitations, Further Research, and Conclusion

Our study provides important insights for both research and practice. However, we acknowledge certain limitations that have to be considered when interpreting the results. First, as the dynamics of crowdfunding are different from those in a traditional e-commerce setting between a seller and a buyer, the applicability to this context might be limited. Second, we believe that the crowdfunding community is not truly representative for other electronic markets, as they can generally be characterized as very internet-savvy. We therefore suspect that the effects of non-genuine social information on the decision-making of a more representative sample might be different, but not necessarily weaker.

Third, even though we used the two largest crowdfunding platforms, we limited the scope of our study to reward-based crowdfunding, which limits the generalizability of our results. Fourth, we were unable to compare the effects of different types of social information in this study, which would further increase the validity of the results. Fifth, we only considered the effects of the occurrence of fake Facebook Likes on the backers. However, one could imagine that fraudulent behavior by few campaign creators could reflect negatively on the rest of the community. Finally, we are aware that our algorithm to identify the acquisition of fake Likes could be an imperfect indicator and might classify very few campaigns as fraudulent even though they are not and vice versa. However, we expect the proportion of these wrongly classified campaigns to be negligible and they should thus not distort our results.

Overall, we believe that this study is an initial step towards understanding the effects of non-genuine social information and that it provides researchers as well as practitioners with useful insights.
References


