Decision Support Systems 90 (2016) 75–85

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

The emergence and effects of fake social information: Evidence from crowdfunding

Michael Wessel *, Ferdinand Thies, Alexander Benlian

Technische Universität Darmstadt, Department of Business, Economics and Law, Chair of Information Systems & E-Services, Hochschulstr. 1, 64289 Darmstadt, Germany

ARTICLE INFO

Article history:
Received 8 September 2015
Received in revised form 29 June 2016
Accepted 30 June 2016
Available online 6 July 2016

Keywords:
Fake social information
Perceived quality
Signaling
Crowdfunding
Facebook Likes

ABSTRACT

In recent years, the growing success of social media has led to a proliferation of social information such as customer product reviews and product ratings in electronic markets. While this information can serve as a quality signal and help 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 mislead consumers deliberately. Consequently, consumers could make suboptimal decisions or choose to disregard social information altogether. Although few studies have been devoted to identifying fake quantitative social information such as fake product rankings and ratings, tracing and examining the effects of such fake information on consumers' actual financial decision-making over time has thus far received only little research attention. In this exploratory study, we assess the effects of non-genuine social information on consumers' 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 platform Kickstarter and observe subsequent campaign performance. Our results show that fake Facebook Likes have a very short-term positive effect on the number of backers funding the respective crowdfunding campaign. However, this short-term peak is followed by an immediate, sharp drop in the number of backers funding the campaign reaching levels that are lower than prior to the occurrence of the non-genuine social information, leading to a total negative effect over time. We further reveal circumstances that foster this artificial manipulation of quality signals, including market and campaign characteristics. Key implications for research and practice are discussed.

1. Introduction

The growing success of social media has led to a proliferation 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 [1]. 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., [2,3]), helping them to overcome the information asymmetry for products whose quality is difficult to ascertain before purchase [4].

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 [5]. 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. 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 qualitative 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 its limited information content, prior research has shown that quantitative social information can have a substantial influence on consumer decision-making (e.g., [6,7]). These studies, however, 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. Furthermore, while other quantitative social information such as product ratings, similar to Facebook Likes, also do not necessarily reflect actual behaviors of consumers, ratings are most often accompanied by

* Corresponding author. Tel.: +49 6151 16 24316; fax: +49 6151 16 24319.
E-mail addresses: wessel@ise.tu-darmstadt.de (M. Wessel), thies@ise.tu-darmstadt.de (F. Thies), benlian@ise.tu-darmstadt.de (A. Benlian).

http://dx.doi.org/10.1016/j.dss.2016.06.021
0167-9236/

reviews. Consumers are therefore able to access additional contextual information such as who contributed the rating, which is impossible in the case of the Facebook Like button. Facebook Likes thus remain 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., [8,9]). This is particularly true for products and services financed through reward-based crowdfunding platforms such as Kickstarter. Here, the so-called backers (i.e., investors or funders) invest in campaigns that appeal to them in the hope to receive adequate tangible rewards for their investment, even though the rewards are not guaranteed legally [10]. In addition to the risk of not receiving a reward at all, the quality of the reward remains unpredictable at the time the backers make an investment decision, because the rewards have not been created yet. Consequently, the utility of the rewards can only be ascertained after the campaign has ended, thus increasing the relevance of quality signals such as the Facebook Like button.

Kickstarter encloses the Facebook Like button 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 [11]. As a consequence, backers on Kickstarter could make suboptimal choices based on the biased information or could choose to disregard or underweight otherwise helpful social information by mistrusting this content altogether [12]. Faking social information has thus become a preeminent threat to the credibility and trustworthiness of this type of user-generated content [13].

While there is a growing stream of research that is focused on uncovering non-genuine qualitative social information (e.g., [14–16]), only few studies have been devoted to identifying fake quantitative social information such as fake product rankings and ratings (e.g., [17,18]). Though these studies offer valuable contributions, tracing and examining the effects of fake quantitative social information on consumer decision-making over time has been difficult because other settings such as e-commerce platforms do not allow researchers to easily observe consumer decision-making after being exposed to fake social information. Against this background, we focus our research on the effects of non-genuine Facebook Likes on the decision-making of prospective backers on the crowdfunding platform Kickstarter over time. 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 encounter fake Likes—a topic which has been largely neglected in previous research on the effects of fake social information. The objective of our study is to address the discussed research gaps guided by the following research questions:

RQ1. How does fake social information in the form of Facebook Likes affect the decision-making of backers on crowdfunding platforms over time?

RQ2. Under what conditions are crowdfunding campaigns more prone to receiving fake Facebook Likes?

To address these research questions, we analyzed more than 35,000 Kickstarter projects during their complete life cycle, covering the period from January to July 2015 and find that 1.6% of all projects receive fake Facebook Likes. Our results show that though a short-term positive effect can be induced by this artificial manipulation of social information, the overall effect is negative. We also find that backers are more likely to encounter fake Facebook Likes in highly crowded categories, when the distribution of funding within a category is uneven, or when the competition is fiercer.

Our results provide important contributions to research and practice. First, while previous studies have primarily focused on identifying *qualitative* fake social information such as fake product reviews (e.g., [14,16]), ours is among the first studies to focus on *quantitative* fake social information to unravel whether and how such information manipulates consumer decision-making over time. While few studies exist that try to identify fake quantitative social information such as fake product rankings and ratings (e.g., [17,18]), our study examines actual financial consequences of fake signals in the form of Facebook Likes based on real-life longitudinal data and thus captures the dynamic and fluctuating patterns of consumer decisions over time. Second, we add to previous research on fake social information by uncovering conditions under which an artificial manipulation of quantitative social information is more or less likely to occur, giving researchers as well as platform providers valuable insights into the relationship between market conditions and unethical behavior. Finally, and more broadly, we are able to confirm that, despite the relative low information content of quantitative social information and even though Facebook Like buttons only reflect preferences and no actual consumer behavior, consumers incorporate these signals into their decision-making and that non-genuine social information thus can have detrimental and undesirable effects. By uncovering these effects, we provide evidence that fake social information should not be overlooked in future studies.

The remainder of the paper is structured as follows: First, we present the theoretical background and develop our hypotheses. We then continue by describing our methodology, including our dataset, regression models, and robustness checks. We then follow-up with our descriptive and econometric evidence and conclude the paper with a discussion of the key findings, contributions and implications, and directions for further research.

2. Theoretical background and hypothesis development

2.1. Information asymmetry and social information as quality signals

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 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 [19]. 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 [4].

Even though physical search costs on the Internet are negligible, they may nevertheless 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 [20]. 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. Consequently, in these situations, in which the seller possesses information that the buyer does not have or in which the buyer is unable to evaluate the quality, the buyer can draw inferences from credible signals sent by the seller [21]. 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 [22]. 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 [23].

Prior research has shown that businesses are able to signal product quality through, for example, advertising and pricing [24]. These signals may become even more credible to the consumers when sent by other consumers instead of businesses [25]. The Internet allows consumers to exchange opinions and recommendations on a large scale through social information such as online customer product reviews. The question of 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 [26] and positive customer product reviews lead to increases in book sales on Amazon [2]. 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. [6] 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 popular ones. Furthermore, Hu et al. [27] find that ratings themselves do not have a significant direct impact on sales of books on Amazon.com, but only indirectly through sentiments. 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 considerably 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 [8].

Despite the growing relevance of social information as a quality signal for consumers, relatively little prior research exists on the effects non-genuine social information might have on consumer decision-making. While numerous studies exist that are focused on uncovering non-genuine qualitative social information (e.g., [14–16]) and few researchers also tried to detect fake quantitative social information such as fake product rankings and ratings through pattern recognition (e.g., [17,18]), we still know little about the effects of fake social information and how it may manipulate consumer decision-making in electronic markets. One of the reasons that this research area is still vastly under-explored is that tracing and examining the effects of fake quantitative social information on consumer decision-making over time has been difficult, as settings such as e-commerce platforms do not allow researchers to observe consumer decision-making after being exposed to fake social information.

Though it is also critical for consumers and e-commerce vendors to know what market conditions can foster unethical behavior such as the creation of fake social information, the amount of research in this area is also limited to few examples. First, Luca and Zervas [13] explore economic incentives to commit review fraud on the popular review platform Yelp.com and find that restaurants are more likely to commit review fraud when their reputation is weak because they either have received few reviews or recently received bad ones. Second, Mayzlin et al. [12] explore and compare review manipulation activities on the popular travel websites Expedia.com and TripAdvisor.com. Their findings suggest that "*actors that are differentially situated economically will indulge in promotional reviewing to a measurably different extent*" [12,p. 2448]. Though these studies offer valuable insights on the emergence of fake *qualitative* social information, the identification of fake *quantitative* social information is considerably more difficult for consumers and e-commerce vendors, making it even more important to uncover conditions under which this artificial manipulation is likely to occur.

2.2. Campaign, creator, and platform characteristics in reward-based crowdfunding

Crowdfunding, the study context in which we investigate our research questions, 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 [28]. It thus creates a large, relatively undefined network of project stakeholders and consequently decreases the importance of other investors such as venture capitalists.

According to an industry report, the combined crowdfunding market was worth $16 billion in 2014 and approximately $34 billion in 2015, with a predicted growth rate of 100% in the following years [29]. The growing success and increased media attention for crowdfunding platforms such as Indiegogo and Kickstarter has made crowdfunding an increasingly attractive alternative for sourcing capital as well as for marketing activities. Besides the benefits for campaign creators, crowdfunding also offers a variety of incentives for backers to "*pledge*" for campaigns. These incentives mainly depend on the return backers can expect from their contributions, which range from donations to company equity [30]. On Kickstarter, the most common and salient type of return is a so-called "*reward*". The rewards can range from small tokens of appreciation (e.g., a thank-you card) for an investment of a few dollars to an early access to the product developed for an investment of hundreds of dollars [31]. Previous research has found these rewards to be a central reason for backers to participate in this so-called reward-based crowdfunding [32]. Consequently, reward-based crowdfunding does not attract investors in the classical sense, but rather consumption-oriented backers, interested in the project or in supporting the cause. In this study, we focus on reward-based crowdfunding, as it is by far the most widespread form of crowdfunding today [29].

Compared to other types of web services, reward-based crowdfunding is special as it allows us to observe the effects of fraudulent social information 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, as there is little to no publicly available and unbiased information about the campaigns [10]. 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 and the updates 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 [33]. 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.

2.3. Fake social information in electronic markets and their effects on consumer decision-making in crowdfunding

A substantial and preeminent threat to the credibility and trustworthiness of social information as a quality signal is the possibility of creating fake data [13]. 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 advertising [34], faking social information is still a growing trend [35]. Acquiring fake Facebook 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 1000 Facebook Likes can be acquired for as little as $15 [36].

Consequently, it remains challenging for providers of online services to identify social information that does not reflect genuine consumer opinions or behavior [12]. Popular websites such as Yelp.com use algorithms to identify and mark specific reviews as fraudulent [14,16]. On Yelp, non-genuine reviews account for 16% of all reviews and tend to be particularly extreme (either favorable or unfavorable) [13]. While consumers might be able to identify fake qualitative content due to its extreme nature and exaggerations contained therein, purely quantitative non-genuine content is generally more difficult to identify by service providers and especially by consumers [17,18]. This is a particular challenge in the context of Facebook Likes as a quality signal, as it remains obscure to the consumer whether the Likes are a genuine signal sent by other consumers or a non-genuine signal sent by sellers. While the 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, providers of online services and consumers will often be unable to quickly identify fake Facebook Likes as such [39,40].

The influence of social information on consumer decision-making is well-established in the IS literature [6,37,38]. Prior research has, for example, shown that the volume of eWOM surrounding a product is an important factor influencing consumers' decision-making processes and that consumers associate higher eWOM volume with a superior product quality [39]. As the investment in crowdfunding campaigns is often required without an existing product or service, the perceived risk rises. This high perceived risk should increase the importance of social information, because with rising search costs and scarcity of information, the relative contribution or importance of the remaining information may increase [4]. 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 [40]. Thus, we expect fake Facebook Likes to have a positive influence on the prospective backer's perception of a campaign's quality because consumers are unable to identify them as being fake, leading to an increase in the number of backers in the following period.

H1. Fake Facebook Likes will lead to an increase in the number of backers pledging for the campaign.

While we expect fake Facebook Likes to positively affect the number of backers contributing to the campaign over time, 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 [9]. Second, fake Facebook Likes are unlikely to attract any additional visitors to the campaign webpage as the fake Facebook accounts created for 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 therefore no real Facebook users will be able to see this information. 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, and updates) reflect that the campaign is of high quality [10]. This would mean that a decelerated growth would follow the positive peak in the number of additional backers. Accordingly, we propose that:

H2. The positive effect of fake Facebook Likes on the number of additional backers will be followed by an immediate, sharp drop in the number of contributors.

The question remains, what characteristics of crowdfunding campaigns, campaign creators, and platforms make it most likely for backers to encounter fake Facebook Likes? 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 [24]. 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 [41]. As these are all characteristics of high quality crowdfunding campaigns, we expect 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. The assessment of campaign quality and the signaling power of these indicators have received considerable attention in recent studies [10,30,42]. Past research has revealed that signals of quality across all crowdfunding models are effective, regardless of backer's expectations for tangible or financial returns [10,42]. Identified indicators of campaign quality include for example, a campaign video, updates, the number of Facebook friends of the creator, [10], the description length, spelling errors, and creator experience [43]. Consequently, campaigns on Kickstarter that provide an entertaining video and offer a detailed and vivid description for the project, offer more rewards, and engage in an active communication with the community, are inherently more shareable [41]. Therefore, these campaigns should receive more genuine Facebook Likes compared to low quality campaigns, making it more likely that the creators of low quality campaigns will try to game the system by acquiring fake Facebook Likes in order to artificially create a quality signal. Consequently, we expect a negative correlation between the quality of individual campaigns and the number of fake Likes they receive.

H3. Campaign quality is associated with a lower likelihood of fake Facebook Likes.

Second, besides the campaign quality that is critical for the backers' evaluation of the campaign directly on Kickstarter, prior research has shown that a viral dissemination of the campaign via social media is crucial for the success of crowdfunding campaigns [9]. Previous research in this context suggest that reaching a critical mass of people who can spread the word about specific information (e.g., a crowdfunding campaign) is more important than being able to reach particularly influential people [44]. Thus, when looking at the characteristics of campaign creators on Kickstarter, those individuals who have an extensive social network should be able to spread the word about their campaign more quickly and broadly [45], generating additional genuine Facebook Likes and making well-connected campaign creators less dependent on an artificial manipulation of Likes. We therefore argue that the extent of the social network the campaign creators have on Facebook negatively influences the emergence of fake Facebook Likes and hypothesize that:

H4. Campaign creators with larger social networks will be less likely to fake Facebook Likes.

Finally, when looking at the crowdfunding platform itself, it can be argued that backers will rarely have to choose between two similar campaigns running at the same time, because campaigns on Kickstarter can most often be characterized as innovative and unique in respect to the project idea. Nevertheless, each campaign has to compete with all other campaigns running at the same time for the attention of prospective backers browsing the specific crowdfunding platform. This is particularly true within the distinct categories (e.g., technology or design) that are used on the platforms to sort and rank campaigns. For example, the most promising campaigns out of each category are listed on the front page of Kickstarter. Consequently, crowded categories (e.g., relatively higher number of campaigns) or concentrated categories (e.g., those hosting few 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 and are more likely to exhibit unethical behavior [12,13,46,47], especially if they perform poorly [48]. As the artificial manipulation of quality signals can be seen as unethical behavior and because truthfulness and honesty are among the rules that campaign creators have to comply with on Kickstarter, an increased competition and market concentration can be expected to lead to an increase in the average number of fake Likes per campaign.

H5a. Fake Facebook Likes will occur more often in crowded categories.

H5b. Fake Facebook Likes will occur more often in concentrated categories.

Similarly, prior research has shown that inequality (e.g., with respect to income distribution) can foster unethical behavior such as corruption [49]. While those on the high end of income distribution try to retain their status by participating in unethical behavior, those at the low end use unethical behavior as a means to narrow the gap between rich and poor [49]. Transferring this notion to our context, creators that receive little funding are more prone to manipulation. This would in turn mean that categories with an uneven distribution of funds are more likely to experience fraud. We therefore argue that, as the inequality of funding rises within a specific category on Kickstarter, more campaign creators will engage in unethical behavior.

H5c. Fake Facebook Likes will occur more often in categories that exhibit a high inequality of funding among the campaigns.

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 sudden increase (i.e., 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 potential backers [50]. In order to explore the effects and premises of non-genuine Facebook Likes, we apply several econometric analyses and provide illustrations to examine our research hypotheses.

3.1. Dataset and identification of campaigns with fake likes

We collected our campaign-level data from Kickstarter, which is the leading and most prominent reward-based crowdfunding platform today. Since Kickstarter's launch in 2009, over $1.8 billion have been pledged by more than 9 million individuals, successfully funding more than 90,000 projects [51]. 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. Our data covers more than 7 months from January 20 to July 28, 2015, including more than 35,000 campaigns.

Campaigns involved in the artificial manipulation of quality signals were identified as such, when unnatural peaks in additional Facebook Likes occurred on a single day and dropped in the same way afterwards. This usage of a temporal pattern is a common method for fraud detection (e.g., [17,18,52]). Jacob and Levitt [52], for example, used a similar technique to detect cheating of teachers and administrators by monitoring score fluctuations in standardized high school tests over consecutive years. Even though peaks in Facebook Likes are to be expected when a campaign receives major attention in other channels, such as blogs or news sites, these natural peaks are then followed by an increased and then gradually declining number of daily Likes over time. Therefore, three conditions were required to safely identify manipulation: First, campaigns had to receive more than the threefold standard deviation of additional Facebook Likes in a single day [53]. Second, the number of new Likes had to exceed 250, as the former rule is impractical for small values and vendors of Facebook Likes commonly sell them in quantities of at least 250 [54]. Third, a significant drop in the additional number of additional daily Facebook Likes had to occur afterwards. Meaning that on the following day, a threefold standard deviation decline has to happen. This sequential ensemble ensures that the additional Likes do not stem from a promotional effort and are in fact manipulated. 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 [53]. Applying the filtering mechanism still resulted in 591 projects that were identified as being involved in fraudulent actions in respect to Facebook Likes. Due to the novelty of this approach in this area, we provide multiple robustness checks for alternative identification conditions.

3.2. Model and variables

In order to test our hypotheses, we calculated three different models: 1) a negative binominal regression with the number of additional backers as our dependent variable to test H1 and H2, 2) a probit model with the dependent dummy variable fake Facebook Likes to test H3 and H4, and 3) a negative binominal regression with the number of campaigns that use fake Facebook Likes per category as the dependent variable to test H5a to H5c.

In our first model, our dependent variable is the number of additional backers a campaign acquires each day, which measures the adoption rate during the life cycle of a campaign. We use the number of additional backers (instead of the dollar amount pledged) on each day as our dependent variable for the following two reasons. First, our intention was to examine the impact of fraudulent behavior on the individual decision to support a campaign and not the amount of funding a backer gives. Second, single and extremely high donations, possibly by the project creators themselves, might severely distort the results. Panel Poisson models are commonly used when the dependent variable is a count. We used negative binominal regression models (NBREG) in our analysis, because the dependent variable is overdispersed, meaning its variance is bigger than its mean [55]. We employ a fixed-effects specification [56] 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 [56]. The following model specification therefore results for our baseline regression:

$$y_{it} = \alpha_i + \beta x_{it} + \gamma z_i \qquad (1-1)$$

where y_{it} is the dependent variable describing the number of backers (y) for each campaign (i) on a single day (t). The individual-effects negative binominal model assumes that y_{it} takes non-negative integer values and is overdispersed. Our independent Fake Like dummy variable turns from 0 to 1 after non-genuine Likes were added for a specific campaign, and is represented by βx_{it}. Here, α_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 [57]. 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. We also controlled for the category of a project, as some might attract more backers than others.

In our baseline model (1–1), we include a before/after dummy for the occurrence of fake Likes, while we use a set of 11 daily dummies in our second specification of the baseline regression (1–2) to create an econometric model that shows the effects 5 days before and after the occurrence of fake Likes [50].

For our second model, we use the occurrence of Fake Likes as a binary dependent variable. 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 [58]. Our model is therefore formalized as follows:

$$p_i = PR[y_i = 1|x_i] = \Phi(\beta_1 + \beta_2 x_i). \qquad (2)$$

Here y_i is the occurrence of fake Facebook Likes (0/1) depending on campaign characteristics and success factors: x_i. In order to assess the proposed influence of campaign quality and market competition, we use several proxy variables in our regression analysis. In this respect, we consider several characteristics of crowdfunding campaigns that allow us to determine how thorough the creator prepared the campaign [59]. One key element here is whether the campaign includes a video [10]. Producing and uploading a video is also strongly recommended by Kickstarter, claiming that campaigns that do not provide a video have a much lower success rate [60].

Another indicator of quality is the number of updates to keep backers informed and engage frequently with the community [32,61]. Additional indicators are the creator experience [62], the duration of the campaign, and the number of offered rewards [32,61]. Furthermore, we evaluate the preparedness by looking at the description length of the campaign, the underlying intuition being that a longer and more detailed description can reduce the information asymmetry better than a shorter description. The social network of the creator, measured by the number of Facebook friends, reflects the initial installed base, the creator can rely on, to back the project and share it with their friends, and therefore increase dissemination [32,61].

For our third model, we again employ a negative binominal panel regression, as we are modeling the number of cheaters within a project category on a single day:

$$y_{it} = \alpha_i + \beta x_{it} + \gamma z_i. \qquad (3)$$

Here y_{it} is the number of projects (y) within a category (i) on a single day (t), dependent on the market conditions x_{it}, category specific fixed effects (α) and an error term (z). In order to assess market condition and competition, we apply three different measures. First, we measure the daily crowdedness of each category by dividing the number of current projects within a category by the average number of projects per category [63]. This measurement captures if a campaign competes with a relatively high or low number of other campaigns within their dedicated category. Second, we calculate the market concentration within project categories to account for the allocation of resources [64]. We used the following Herfindahl–Hirschman Index (HHI) from strategic management research as our measure:

$$HHI = \sum\nolimits_i^N b_{it}^2$$

where b_i is the fraction of a campaign's total backings (i.e., number of backers) in the project category (i) at time t. This measure ranges from $1/N$ to 1, where N is the total number of campaigns in a given category. For example, if a campaign has received all funds invested within a specific category, then this measure is 1 and the category is maximally concentrated [64,65]. The HHI captures whether a category is dominated by a few campaigns compared to an even distribution among all participants.

Third, we are looking at the distribution of daily pledges across all projects within a category. We use the Gini coefficient to measure the inequality of distribution of pledges among projects in a category, which is usually applied in economic and sociology literature. The Gini coefficient derives from the Lorenz curves and is calculated as follows:

$$G = 1\text{-}\frac{1}{n}\sum_{i=1}^{n}(y_{i\text{-}1} + y_i)$$

where i is the project's rank order number, n is the number of total projects within a category, y_i is the project's received share of total pledges within its category. The Gini coefficient ranges from 0 to 1, where a value of 0 represents a perfectly even distribution of pledges among all projects, and a Gini of 1 meaning that only one project receives the total pledges in the category on a single day [49].

3.3. Robustness checks

To check for robustness of our fake Like identification approach, we tightened the algorithm to determine fraudulent behavior to a fourth fold standard deviation with a threshold of 500 Facebook Likes, resulting in 162 projects and loosened the restriction to a double standard deviation and a threshold of 100 leaving 2279 projects. Both specifications produced identical result patterns, showing that our measurement is robust to a tighter and looser configuration.

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. Furthermore, we employed a clustered zero inflated Poisson regression (ZIP) as an alternative estimator. 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 NBREG for backing behavior, the probit regression for campaign characteristics and the NBREG for market conditions. 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.

We present the results of our main model Table 2, which provides evidence for the effects of fake social information on the backing behavior of the crowdfunding community. We continue with our probit model in Table 3 to show what factors of a crowdfunding campaign influence the occurrence of fake Facebook Likes. We conclude our analysis with the NBREG for market conditions (Table 4).

4.1. Descriptive evidence

Before we focus on answering our main research questions, we first highlight relevant descriptive statistics for all campaigns and for those affected by the artificial manipulation of Facebook Likes measured at the end of the campaign life cycle (Table 1). Compared to all campaigns, we observe a higher number of backers, more funding, and higher funding goals for the 591 campaigns that received fake Facebook Likes.

Table 1
Summary statistics for the complete dataset and for campaigns that received fake Facebook Likes.

Complete dataset (N = 36,543)	Mean	SD	Min	Max
Fake Likes (dummy)	0.016	0.13	0	1
Facebook Likes	205.49	1530.27	0	168,630
Backers	63.33	619.01	0	78,471
Accumulated funding	5950.73	115,823	0	2.03e + 07
Funding goal	74,417.24	1,591,930	1	1.00e + 08
Campaign duration (days)	33.04	11.64	1	73
Number of rewards	6.41	5.62	0	146
Description length (characters)	2724.99	3195.79	0	34,667
Video	0.53	0.50	0	1
Updates	1.81	3.84	0	107
Campaigns created	1.332	1.58	1	69
Facebook friends	626.93	847.53	0	5291
Crowdedness	1.90	0.95	0.0031	4.16
Inequality (Gini coefficient)	0.66	0.14	0.23	0.91
Concentration (HHI)	0.083	0.092	0	1
Fake Like campaigns (N = 591)	Mean	SD	Min	Max
Facebook Likes	2977.12	8351.24	263	168,630
Backers	529.80	2219.94	0	45,815
Accumulated funding	48,288.99	170,824.80	0	2,950,874
Funding goal	204,397.40	3,318,139	350	8.0e + 07

We continue by calculating the percentage of campaigns that engaged in the acquisition of fake Likes within each distinctive category as depicted in Fig. 1. We see that certain categories such as Design, Comics, Film & Video, and Technology are much more prone to altering their Facebook Likes compared to categories such as Crafts, Journalism, Art and Food. Still, competition in the latter might be less fierce, which could mitigate the need for unethical behavior.

As we are using a panel dataset, we are able to identify the exact date a campaign received the non-genuine Facebook Likes. Fig. 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 genuine development. Though genuine Likes can exhibit natural peaks (Fig. 2), these peaks are not followed by a significant and sharp drop, which can therefore be used to identify fake Likes.

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 (Fig. 3). Each circle 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 see that the majority of creators try to increase the odds of success by making use of the artificial manipulation of Facebook Likes early in the campaign's life cycle, represented by the dense cluster in the lower left corner. This is in line with findings on manipulative reviews which are commonly posted close to the launch of a product [15]. The reference line assumes a linear increase of funding during the campaign life cycle. Drawing from the representation in Fig. 3, we can also see that most campaigns are above the reference line. This indicates that the manipulation hurts their funding progress, as they necessarily end up in the upper right corner at the end of their campaign. Several campaigns were even unable to attract any additional funding after the manipulation of Likes, as represented by the dots on the top end.

4.2. Econometric evidence

4.2.1. Dynamic effects of fake social information on decision-making

We now turn to our econometric evidence and the hypotheses testing for the effects of fake social information (in the form of Facebook

Table 2
Results from NBREG for additional backers.

Δ Backers	Model (1–1)	Model (1–2)
Fake Likes (dummy)	− 0.286*** (− 14.723)	
Updates	− 0.027*** (− 10.712)	− 0.012 (− 1.856)
Campaign category	Included	Included
T-5		0 (0.0)
T-4		− 0.074 (− 1.074)
T-3		− 0.135 (− 1.959)
T-2		0.005 (0.076)
T-1		− 0.048 (− 0.793)
T		0.689*** (11.964)
T + 1		0.089 (1.465)
T + 2		− 0.174** (− 2.749)
T + 3		− 0.315*** (− 4.853)
T + 4		− 0.322*** (− 4.939)
T + 5		− 0.423*** (− 6.324)
Constant	− 0.146 (− 1.689)	0.071 (0.394)
BIC	95,731	24,874
Log likelihood	− 47,781	− 12,326
Wald Chi^2	582	1016
Campaigns	582	563
Observations	20,090	5132

Notes: *t* statistics in parentheses.
** $p < 0.01$.
*** $p < 0.001$.

Table 3
Results from the probit regression for occurrence of fake Facebook Likes.

Fake Likes (dummy)	Model (2–1)	Model (2–2)
Campaign duration (days)	0.004* (2.555)	0.007** (2.748)
ln (funding goal)	0.120*** (9.514)	0.129*** (7.010)
ln (number of rewards)	0.389*** (12.347)	0.370*** (8.043)
Campaign updates	0.031*** (9.775)	0.027*** (6.371)
Description length (characters)	0.195e − 6*** (4.149)	0.166e − 6* (2.368)
Video	0.288*** (5.467)	0.159* (2.154)
Campaigns created	− 0.013 (− 0.818)	− 0.022 (− 1.034)
Facebook profile	− 0.045 (− 1.187)	
ln (number of Facebook friends)		0.149*** (6.866)
Campaign category	Included	Included
Constant	− 4.676*** (− 27.717)	− 5.757*** (− 20.188)
BIC	5190	2631
Log likelihood	− 2474	− 1203
Wald Chi^2	1099	594
Pseudo R^2	0.182	0.198
Observations	36,541	17,915

Notes: *t* statistics in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 4
Results from NBREG for number of campaigns with fake Facebook Likes.

Campaigns with fake Likes (count)	Model (3)
Crowdedness	0.328*** (4.470)
Inequality (Gini coefficient)	5.213*** (6.729)
Concentration (HHI)	−2.975*** (−3.731)
Constant	−2.083** (−2.621)
BIC	2645
Log likelihood	−1306
Wald Chi^2	108
Categories	15
Observations	2848

Notes: *t* statistics in parentheses.
** $p < 0.01$.
*** $p < 0.001$.

Likes) on the decision-making of prospective backers on Kickstarter over time. We ran our first model for our econometric results as depicted in Table 2.

Model specification 1–1 includes a before/after dummy for the purchase of Fake Likes. In order to model the dynamic effects and to rule out rival explanations (1–2), we created a set of time-related dummies for the 5 days before, after and on the day of the artificial manipulation. Observations in Model 1–2 are thus restricted to be within an 11-day time period from the purchase of Fake Likes.

For our first hypothesis, we consider the negative and significant coefficient of the *Fake Likes Dummy* in specification 1–1, clearly indicating a negative effect of non-genuine Facebook Likes. Consequently, campaign creators who try to increase the odds of success for their campaigns by acquiring fake Likes do in fact achieve the opposite, contrasting our expectation. However, when looking at the dynamic effects in model 1–2, we can observe a positive and significant coefficient for the first day following the artificial manipulation of Likes as we expected. In our second hypothesis we argued that any positive effect will, however, be very short lived. In model 1–2 we see the predicted subsequent sharp drop in funding activities represented by the consecutively negative coefficient after $T + 1$. This decline may be attributable to the possibility that backers who planned to participate anyway simply expedited their investment based on the non-genuine social information (H2). Due to this trigger, other quality indicators such as the number of backers, pledge amount or updates might lose their relevance in the aftermath of fake Facebook Likes. Fig. 4 illustrates the development of additional backers per day before and after the occurrence of fake Facebook Likes.

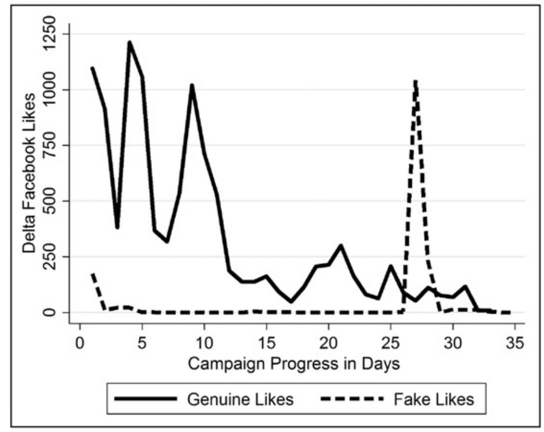

Fig. 2. Example of genuine and non-genuine peaks in Facebook Likes.

4.2.2. Conditions for the emergence of fake social information

While the effects of the fake social information on the decision-making of backers revealed interesting insights, we will now investigate the circumstances under which campaigns with fake Likes are most prevalent. For our third hypothesis, we argued for a negative relation of the quality of individual campaigns and the number of fake Likes. In order to test whether any correlation exists between the characteristics or the quality of individual campaigns and the likelihood of any artificial manipulation of quality signals, we used a probit model (2–1 and 2–2) with the occurrence of fake Facebook Likes as the binary dependent variable. Results are shown in Table 3. Though the model 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 the occurrence of fake Likes.

One of the key elements of every crowdfunding campaign on Kickstarter 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 an in contrast to our hypothesis, we see that, if a video exists, the artificial manipulation of social information becomes more likely. The same is true for other quality signals such as the number of updates a creator provides during the campaign life cycle, the number of rewards, and the description length (see Table 3).

For our fourth hypothesis, we argued that creators with an extensive personal social network are less likely to engage in an artificial manipulation of Facebook Likes, as they should be able to spread the word about

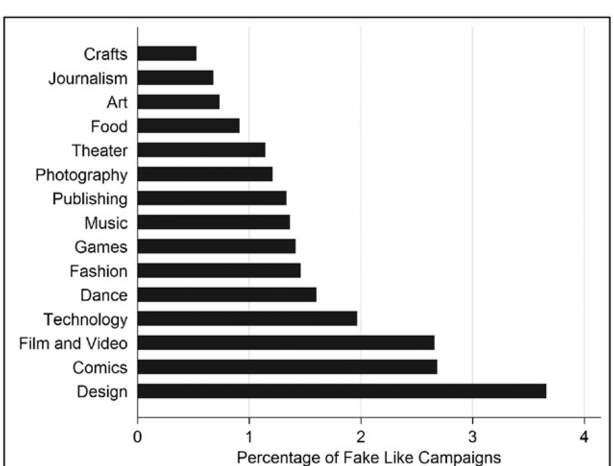

Fig. 1. Percentage of campaigns in the distinct categories on Kickstarter that received non-genuine Facebook Likes during the campaign life cycle.

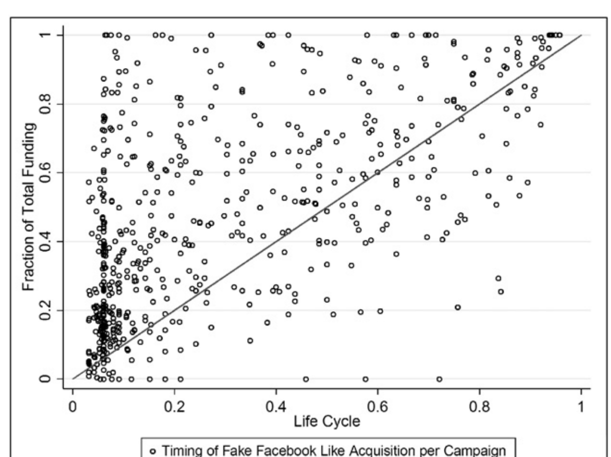

Fig. 3. Timing of unnatural peaks with respect to funding and life cycle.

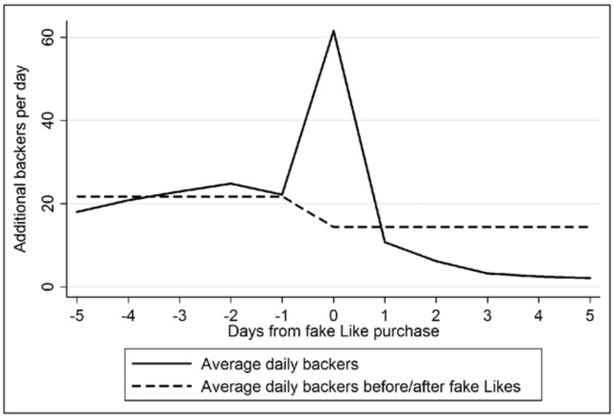

Fig. 4. Average daily backers per campaign before and after fake Likes.

their campaigns more quickly and easily, therefore having no need for non-genuine Facebook Likes. Contrasting our hypothesis, we see a positive coefficient in specification 2–2 meaning that creators with a larger social network are also more likely to acquire fake Facebook Likes.[1]

We identified unnatural peaks in 1.6% of the campaigns on Kickstarter. Still, we showed in Fig. 1 that these campaigns are not evenly distributed over the campaign categories. This difference was expected due to the different conditions within the campaign categories (H5a to H5c). We proposed that, as the intensity of competition within a category increases, campaign creators will be less likely to follow the market rules and more likely to acquire fake Likes. We thus measured the dynamic market crowdedness, market concentration (Herfindahl–Hirschman Index), and inequality of daily pledges (Gini-Coefficient) for every category on each day in order to determine the intensity of competition. We therefore used a negative binominal regression model with the number of campaigns with Fake Likes as dependent variable and the three market conditions within each category as independent variable. The results in Table 4 suggest that, on Kickstarter, an increased market crowdedness does in fact increase the likelihood of artificial manipulations of social information in the respective category. This finding supports H5a. Contrary to H5b, backers are less likely to face manipulated Facebook Likes within categories where the funding is heavily concentrated on a few campaigns. Finally, artificial manipulations will occur more often in categories that exhibit a high inequality of funding measured by the Gini coefficient, providing support for the final hypothesis H5c.

5. Discussion and contributions

After reviewing our descriptive and econometric evidence, we will now link these results to our initial research questions. For our first research question, we investigated how fake social information in the form of Facebook Likes affects the decision-making of backers on crowdfunding platforms over time. Our analysis clearly shows that non-genuine social information does in fact influence the investment decisions of backers. The negative coefficient however shows that, overall, manipulation activities have a negative effect on backing behavior and thus virtually backfire, as the campaign creators achieve the opposite of what they originally 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 acquiring fake Facebook Likes could induce a short-term gain in backers. 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 investment decisions based on the observed peak. It is therefore reasonable to expect that a positive peak in backers is directly followed by a sharp drop and decelerated growth rate in backers over time.

For our second research question, we present several factors that potentially increase the likelihood of artificial manipulations of quality signals. First, our descriptive evidence shows that categories that include 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 [9,41] and creators of campaigns in these categories therefore see less need to acquire additional Facebook Likes. Second and contrary to our expectations, creators who invest more time and effort in creating and managing their campaign are more prone to acquiring fake Facebook 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 that they game the system and draw on unethical behaviors. Furthermore, project creators of low quality campaigns might be reluctant to heavily manipulate social information due to the rational expectation effect, meaning that, with an increasing discrepancy between the number of Facebook Likes and the quality of the respective campaign, more consumers will discount any information they receive [66]. Third, we see that the conditions within the distinctive categories strongly influence the behavior of campaign creators with respect to an artificial manipulation of quality signals. Stronger competition increases the likelihood of fake Facebook Likes, while, contrary to our expectations, categories that are more concentrated are less susceptible to manipulations. A reason might be that creators who face competing campaigns of extremely high quality accept their fate more easily and are therefore more reluctant to manipulate their quality signals. On the other hand, a seemingly unfair distribution of pledges among the campaigns within a specific category fosters manipulations. Finally, we also provide evidence for the timing of the acquisition of fake Likes with respect to the funding raised and the campaign life cycle and found that the majority of creators acquire non-genuine Likes early in the campaign's life cycle and many are unable to generate above-average funding afterwards.

5.1. Contributions to theory and research

To the best of our knowledge, ours is among the first studies focusing on the effects of quantitative fake social information on consumer decision-making in electronic markets using real-life longitudinal data. Although few previous studies have focused on the identification of fake quantitative social information, virtually no research has investigated the temporal effects that fake quantitative social information can have on consumer decision-making (e.g., [17,18]).Therefore, our study makes several interesting contributions to theory and research. First, we shed light on the dynamic short- and long-term effects of fake social information in electronic markets by empirically showing that, even though a short-term positive effect can be induced by an artificial manipulation of social information, the overall effect is negative. This result is especially interesting and novel as prior research has found that genuine social information has a positive (or no effect) on consumer decision-making (e.g., [2,3]), which has also been shown for genuine Facebook Likes/Shares in the context of crowdfunding (cf., [9]). Due to these contradictory effects, the potentially distorting effects of non-genuine social information should be taken into account in similar research settings in the future.

[1] About 50% of creators connected their Facebook profile to their campaign, which enabled us to include the number of friends as a variable. Results in specification 2–2 include the number of Facebook friends of the creator, while 2–1 includes a dummy, if the creator connected their Facebook profile.

Second, we uncovered market and product conditions under which an artificial manipulation of quantitative social information is likely to occur. Even though there is a growing stream of research focused on uncovering non-genuine qualitative social information (e.g., [14,16]), these studies have, with few exceptions (e.g., [12,13]), neglected the circumstances under which this content is more or less likely to occur. As such, our study adds to previous research on fake social information by uncovering important boundary conditions for the detrimental effects of fake information on consumer decision-making. Furthermore, while past studies have largely focused on experimental data with cross-sectional and attitudinal outcomes, we were able to demonstrate the actual and binding consequences of fake social information in a real-life setting with observational data over several months. We therefore hope that, by uncovering these important boundary conditions for artificial manipulations, our study provides impetus for further research in this context. Finally, and more broadly, we were able to confirm that, despite its relatively low information content, quantitative (fake) social information can have a substantial effect on consumer decision-making. This reveals 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 and information systems research by advancing our understanding of the differential effects social information can have on consumers and by highlighting the role of artificial manipulations and its dynamic fluctuating (i.e., positive and negative) effect patterns over time.

5.2. Practical implications

We also see practical implications that should be considered by the creators of campaigns and by the providers of crowdfunding platforms. 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 does not attract any additional backers because, unlike genuine Facebook Likes, fake Likes do not disseminate through Facebook's social network. Therefore, this artificial manipulation of quality signals can only affect users who see the Facebook Like button directly on the webpage and who visit the campaign webpage anyway for other reasons. Even though we see that a short term gain can be induced, our findings demonstrate that non-genuine Facebook Likes have a negative effect on the outcome of crowdfunding campaigns.

For platform providers, our study provides insights on both the extent of manipulation as well as under what conditions and campaign characteristics it is most prevalent. Though our results might help platform providers to identify campaign creators who acquire non-genuine social information, punishing their actions might not be necessary because, according to our findings, they do not gain an advantage over honest campaign creators. Still, manipulative actions might hurt the overall reputation of the platform and long-term effects need to be considered.

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. Even though we used a large dataset over a long period of time, we limited the scope of our study to Kickstarter, which also narrows the generalizability of our results. 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, we were unable to compare the effects of different types of social information (e.g., Twitter Tweets) in this study, which would further increase the validity of the results. Fourth, we only considered the effects of the occurrence of fake Facebook Likes on backers. However, one could imagine that fraudulent behavior by a few black sheep among the campaign creators could be contagious and spill over to the rest of the community, thus creating negative externalities for the entire ecosystem. Finally, we are aware that our algorithm to identify the acquisition of fake Likes is not a perfect indicator and might classify very few campaigns as fraudulent even though they are not and vice versa, equivalent to false positive (Type I) and false negative (Type II) errors of a diagnostic system. However, in several robustness checks, we altered the fake Likes identification algorithm to tighter and looser configurations and received identical result patterns. We therefore expect the proportion of these wrongly classified campaigns to be negligible and they should thus not distort our results.

Overall, our study reveals that manipulated social information has a very short-term positive effect on backers' funding decision in a crowdfunding campaign. However, this short-term peak is followed by an immediate, sharp drop in the number of backers funding the campaign reaching levels that are lower than prior to the occurrence of the non-genuine social information, leading to a total negative effect over time. Additionally, we provide evidence that market conditions and campaign characteristics play an important role in shaping the likelihood of manipulations to occur on a crowdfunding platform. We hope that this study will serve as a springboard for future research on the effects of non-genuine social information in electronic markets and give food for thought to the diverse stakeholders of platform ecosystems.

Acknowledgments

The work described in this paper was supported by a grant from the Dr. Werner Jackstädt Foundation in Germany (Grant No. 010103/56300720).

References

[1] P.A. Pavlou, H. Liang, Y. Xue, Understanding and mitigating uncertainty in online exchange relationships: a principal–agent perspective, MIS Quarterly 31 (1) (2007) 105–136.
[2] J.A. Chevalier, D. Mayzlin, The effect of word of mouth on sales: online book reviews, Journal of Marketing Research 43 (3) (2006) 345–354.
[3] W. Duan, B. Gu, A.B. Whinston, The dynamics of online word-of-mouth and product sales — an empirical investigation of the movie industry, Journal of Retailing 84 (2) (2008) 233–242.
[4] G.A. Akerlof, The market for "lemons": quality uncertainty and the market mechanism, The Quarterly Journal of Economics 84 (3) (1970) 488–500.
[5] Built with, Facebook like usage statistics, http://trends.builtwith.com/widgets/Facebook-Like2014.
[6] W. Duan, B. Gu, A.B. Whinston, Informational cascades and software adoption on the internet: an empirical investigation, MIS Quarterly 33 (1) (2009) 23–48.
[7] C. Tucker, J. Zhang, How does popularity information affect choices? A field experiment, Management Science 57 (5) (2011) 828–842.
[8] V. Schöndienst, F. Kulzer, O. Günther, Like versus dislike: how Facebook's Like-button influences people's perception of product and service quality, Thirty Third International Conference on Information Systems, Orlando, 2012.
[9] F. Thies, M. Wessel, A. Benlian, Understanding the dynamic interplay of social buzz and contribution behavior within and between online platforms — evidence from crowdfunding, International Conference on Information Systems (ICIS 2014), Auckland, New Zealand, 2014.
[10] E. Mollick, The dynamics of crowdfunding: an exploratory study, Journal of Business Venturing 29 (1) (2014) 1–16.
[11] Facebook Inc., What are fake page likes? https://www.facebook.com/help/1540525152857028 2015.
[12] D. Mayzlin, Y. Dover, J. Chevalier, Promotional reviews: an empirical investigation of online review manipulation, American Economic Review 104 (8) (2014) 2421–2455.
[13] M. Luca, G. Zervas, Fake it till you make it: reputation, competition, and yelp review fraud, Management Science (2016) (forthcoming, http://pubsonline.informs.org/doi/abs/10.1287/mnsc.2015.2304).
[14] N. Jindal, B. Liu, E.-P. Lim, Finding unusual review patterns using unexpected rules, Proceedings of the 19th ACM International Conference on Information and Knowledge Management 2010, pp. 1549–1552.
[15] N. Hu, I. Bose, Y. Gao, L. Liu, Manipulation in digital word-of-mouth: a reality check for book reviews, Decision Support Systems 50 (3) (2011) 627–635.

[16] F. Li, M. Huang, Y. Yang, X. Zhu, Learning to identify review spam, IJCAI Proceedings—International Joint Conference on Artificial Intelligence, 2011.
[17] S. Xie, G. Wang, S. Lin, P.S. Yu, Review spam detection via temporal pattern discovery, Proceedings of the 18th ACM SIGKDD Conference on Knowledge Discovery and Data Mining2012.
[18] H. Zhu, H. Xiong, Y. Ge, E. Chen, Discovery of ranking fraud for mobile apps, IEEE Transactions on Knowledge and Data Engineering 27 (1) (2015) 74–87.
[19] T. Mavlanova, R. Benbunan-Fich, M. Koufaris, Signaling theory and information asymmetry in online commerce, Information Management 49 (5) (2012) 240–247.
[20] B.C. Krishnan, M.D. Hartline, Brand equity: is it more important in services? Journal of Services Marketing 15 (5) (2001) 328–342.
[21] D. Biswas, A. Biswas, The diagnostic role of signals in the context of perceived risks in online shopping: do signals matter more on the web? Journal of Interactive Marketing 18 (3) (2004) 30–45.
[22] H.R. Yen, Risk-reducing signals for new online retailers: a study of single and multiple signalling effects, International Journal of Internet Marketing and Advertising 3 (4) (2006) 299–317.
[23] M. Spence, Job market signaling, The Quarterly Journal of Economics 87 (3) (1973) 355–374.
[24] A. Kirmani, A.R. Rao, No pain, no gain: a critical review of the literature on signaling unobservable product quality, Journal of Marketing 64 (2) (2000) 66–79.
[25] J. Brown, A.J. Broderick, N. Lee, Word of mouth communication within online communities: conceptualizing the online social network, Journal of Interactive Marketing 21 (3) (2007) 2–20.
[26] Y. Liu, Word of mouth for movies: its dynamics and impact on box office revenue, Journal of Marketing 70 (3) (2006) 74–89.
[27] N. Hu, N.S. Koh, S.K. Reddy, Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales, Decision Support Systems 57 (2014) 42–53.
[28] A. Schwienbacher, B. Larralde, Crowdfunding of small entrepreneurial ventures, The Oxford Handbook of Entrepreneurial Finance, Oxford University Press, 2012.
[29] Massolution, The crowdfunding industry report, http://www.crowdsourcing.org/editorial/global-crowdfunding-market-to-reach-344b-in-2015-predicts-massolutions-2015cf-industry-report/453762015.
[30] G.K.C. Ahlers, D. Cumming, C. Günther, D. Schweizer, Signaling in equity crowdfunding, Entrepreneurship Theory and Practice 39 (4) (2015) 955–980.
[31] P. Belleflamme, T. Lambert, A. Schwienbacher, Crowdfunding: tapping the right crowd, Journal of Business Venturing 29 (5) (2014) 585–609.
[32] V. Kuppuswamy, B.L. Bayus, Crowdfunding creative ideas: the dynamics of project backers in Kickstarter, Working Papers/UNC Kenan-Flagler Research Paper No. 2013–15, 2014.
[33] G. Burtch, A. Ghose, S. Wattal, An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets, Information Systems Research 24 (3) (2013) 499–519.
[34] Federal Trade Commission, Guides concerning the use of endorsements and testimonials in advertising, In: 16 CFR Part 255 (2009) (Federal Trade Commission).
[35] J. Sussin, E. Thompson, The Consequences of Fake Fans, 'Likes' and Reviews on Social Networks, Gartner Research, 2012.
[36] C. Arthur, How low-paid workers at 'click farms' create appearance of online popularity, http://www.theguardian.com/technology/2013/aug/02/click-farms-appearance-online-popularity2013.
[37] C.M.K. Cheung, B.S. Xiao, I.L.B. Liu, Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions, Decision Support Systems 65 (2014) 50–58.
[38] W. Duan, B. Gu, A.B. Whinston, Do online reviews matter? — An empirical investigation of panel data, Decision Support Systems 45 (4) (2008) 1007–1016.
[39] N. Amblee, T. Bui, Harnessing the influence of social proof in online shopping: the effect of electronic word of mouth on sales of digital microproducts, International Journal of Electronic Commerce 16 (2) (2011) 91–114.
[40] M. Spence, Signaling in retrospect and the informational structure of markets, The American Economic Review 92 (3) (2002) 434–459.
[41] J. Berger, K.L. Milkman, What makes online content viral? Journal of Marketing Research 49 (2) (2012) 192–205.
[42] G. Burtch, A. Ghose, S. Wattal, The hidden cost of accommodating crowdfunder privacy preferences: a randomized field experiment, Management Science 61 (5) (2015) 949–962.
[43] M. Wessel, F. Thies, A. Benlian, The effects of relinquishing control in platform ecosystems: implications from a policy change on Kickstarter, International Conference on Information Systems (ICIS 2015), Fort Worth, Texas, 2015.
[44] D.J. Watts, P.S. Dodds, Influentials, networks, and public opinion formation, Journal of Consumer Research 34 (4) (2007) 441–458.
[45] O. Hinz, B. Skiera, C. Barrot, J.U. Becker, Seeding strategies for viral marketing: an empirical comparison, Journal of Marketing 75 (6) (2011) 55–71.
[46] F. Branco, J.M. Villas-Boas, Competitive vices, Journal of Marketing Research 52 (6) (2015) 801–816.
[47] B.W. Kulik, M.J. O'Fallon, M.S. Salimath, Do competitive environments lead to the rise and spread of unethical behavior? Parallels from Enron, Journal of Business Ethics 83 (4) (2008) 703–723.
[48] C. Schwieren, D. Weichselbaumer, Does competition enhance performance or cheating? A laboratory experiment, Journal of Economic Psychology 31 (3) (2010) 241–253.
[49] Y. Jong-Sung, S. Khagram, A comparative study of inequality and corruption, American Sociological Review 70 (1) (2005) 136–157.
[50] J. Claussen, T. Kretschmer, P. Mayrhofer, The effects of rewarding user engagement: the case of Facebook apps, Information Systems Research 24 (1) (2013) 186–200.
[51] Kickstarter, Inc., Kickstarter stats, https://www.kickstarter.com/help/stats2015.
[52] B.A. Jacob, S.D. Levitt, Catching Cheating Teachers: the Results of an Unusual Experiment in Implementing Theory, National Bureau of Economic Research, 2003.
[53] C.C. Aggarwal, Outlier Analysis, Springer, New York, 2013.
[54] E. Steuer, How to buy friends and influence people on Facebook, http://www.wired.com/2013/04/buy-friends-on-facebook/2013.
[55] A.C. Cameron, P.K. Trivedi, Regression Analysis of Count Data, Cambridge University Press, Cambridge, 2013.
[56] J.A. Hausman, W.E. Taylor, Panel data and unobservable individual effects, Econometrica 49 (6) (1981) 1377–1398.
[57] P.D. Allison, R.P. Waterman, Fixed-effects negative binomial regression models, Sociological Methodology 32 (2002) 247–265.
[58] A.C. Cameron, P.K. Trivedi, Microeconometrics: Methods and Applications, Cambridge University Press, 2005.
[59] X.-P. Chen, X. Yao, S. Kotha, Entrepreneur passion and preparedness in business plan presentations: a persuasion analysis of venture capitalists' funding decisions, Academy of Management Journal 52 (1) (2009) 199–214.
[60] Kickstarter, Inc., Creator Handbook, https://www.kickstarter.com/help/handbook/2015.
[61] A.K. Agrawal, C. Catalini, A. Goldfarb, The Geography of Crowdfunding, National Bureau of Economic Research Working Paper Series No. 168202011.
[62] J. Zhang, The roles of players and reputation: Evidence from eBay online auctions, Decision Support Systems 42 (3) (2006) 1800–1818.
[63] R.K. Chellappa, V. Sambamurthy, N. Saraf, Competing in crowded markets: multimarket contact and the nature of competition in the enterprise systems software industry, Information Systems Research 21 (3) (2010) 614–630.
[64] M.T. Hansen, M.R. Haas, Competing for attention in knowledge markets: electronic document dissemination in a management consulting company, Administrative Science Quarterly 46 (1) (2001) 1–28.
[65] A.O. Hirschman, The paternity of an index, American Economic Review 54 (5) (1964) 761–762.
[66] S.-Y. Lee, L. Qiu, A. Whinston, Manipulation: Online Platforms' Inescapable Fate, International Conference on Information Systems (ICIS 2014), Auckland, New Zealand, 2014.

Michael Wessel is a PhD candidate at the chair of Information Systems and Electronic Services, at Technische Universität Darmstadt (TU Darmstadt), Germany. He holds a Masters' degree in Business Information Systems from the University of Amsterdam. His research interests include web personalization and crowdfunding. His work has been published in international conferences such as International Conference on Information Systems (ICIS) and European Conference on Information Systems (ECIS).

Ferdinand Thies is a PhD candidate at the chair of Information Systems and Electronic Services, at Technische Universität Darmstadt (TU Darmstadt), Germany. He holds a Masters' degree in Business Administration from the University of Munich. His research interests include software platforms and crowdfunding. His work has been published in international conferences such as International Conference on Information Systems (ICIS) and European Conference on Information Systems (ECIS).

Alexander Benlian is a chaired professor of Information Systems and Electronic Services, at Technische Universität Darmstadt (TU Darmstadt), Germany. His work has been published in international journals such as Journal of Management Information Systems, Journal of Service Research, Decision Support Systems, International Journal of Electronic Commerce, Journal of the Association for Information Systems, European Journal of Information Systems, Information Systems Journal, and Journal of Business Economics. His research interests include software platforms, software-as-a-service, and digital business models.