Understanding the Dynamic Interplay of Social Buzz and Contribution Behavior within and between Online Platforms – Evidence from Crowdfunding

Completed Research Paper

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Abstract

Motivated by the growing interconnection between online platforms, we examine the dynamic interplay between social buzz and contribution behavior in the crowdfunding context. Since the utility of crowdfunding projects is usually difficult to ascertain, prospective backers draw on quality signals, such as social buzz and prior-contribution behavior, to make their funding decisions. We employ the panel vector autoregression (PVAR) methodology to investigate both intra- and cross-platform effects based on data collected from three platforms: Indiegogo, one of the largest crowdfunding platforms on the web, Twitter and Facebook. Our results show a positive influence of social buzz on project backing, but a negative relationship in the reverse direction. Furthermore, we observe strong positive feedback cycles within each platform. Our results are supplemented by split-sample analyses for project orientation (Social, Cause and Entrepreneurial) and project success (Winners vs. Losers), in which Facebook shares were identified as a critical success factor.

Keywords: Social media, electronic word-of-mouth, social buzz, contribution behavior, informational cascades, crowdfunding, panel vector autoregression
# Introduction

Crowdfunding allows individuals and organizations to raise funds for a diversity of projects through an open call on the Internet. Compared to the traditional approach of fundraising, crowdfunding is focused on collecting rather small contributions from a large number of individuals. According to an industry report, the combined crowdfunding market was worth about $5 billion and achieved a growth rate beyond 80% in 2013 (Kartaszewicz-Grell et al. 2013). The recent success of crowdfunding platforms such as Indiegogo and Kickstarter has made crowdfunding an increasingly attractive alternative for sourcing capital and has resulted in significant attention for the concept among academics as well as practitioners.

As crowdfunding platforms are two-sided markets, network effects between the project creators and supporters (backers) are prevalent (Eisenmann et al. 2006). While project creators seek to attract backers by creating compelling campaigns, prospective backers often need to make their investment decisions based on limited and potentially biased information provided by the creator. Furthermore, there is usually no legal obligation for the creator of a reward-based crowdfunding campaign to actually deliver the advertised merit (Mollick 2014). Fortunately, today’s social web offers information that helps prospective backers to evaluate the trustworthiness of a crowdfunding project. In this regard, prior-contribution behaviors, in the form of the number of previous backers, and social buzz, equivalent to eWOM on social media platforms such as Facebook and Twitter, are important quality signals for a campaign. Inferring project quality from these signals leads to informational cascades, an information-based explanation for herd behavior that occurs when individuals who face a certain decision choose to follow the actions of others who faced the same decision earlier on, instead of taking a decision based on their own private information (Bikhchandani et al. 1992; Bikhchandani et al. 1998; Duan et al. 2009).

Previous research has shown that informational cascades occur regularly on the Internet, especially when adopting goods whose value can only be ascertained after the purchase (e.g., Duan et al. 2009). Likewise, Zhang and Liu (2012) and Herzenstein et al. (2011) have found that in equity- and lending-based crowdfunding markets, individuals tend to contribute to projects that already have a lot of support from the community to reduce their own risk in the face of uncertainty about the proposed new project. Burtch et al. (2013) have shown that in donation-based markets, prior contribution leads to a substitution effect, as potential backers see less “need” to support the specific project, as it has already received sufficient attention. However, it remains unclear what dynamics prevail in reward-based crowdfunding markets and whether positive or negative informational cascades occur. Furthermore, to our best knowledge, no prior work has examined the dynamic interplay of eWOM and contribution behaviors, and the resulting cross-platform effects in reward-based crowdfunding markets in depth and thus our current understanding of the underlying dynamics is far from conclusive (Thies and Wessel 2014). Our research is further motivated by Burtch et al. (2013) who called for additional research on reward-based crowdfunding platforms and explicitly suggested investigating popularity indicators, behavioral signals, and subsequent project performance. Furthermore, Veit et al. (2014) call for additional research on the proactive role of consumers and the effects of social recommendations.

Against this background, we focus our research on the reciprocal relationship between social buzz, prior-contribution behavior and consumer decision-making. Additionally, we investigate the interplay of social buzz and project backing also in different project categories. In doing so, we are able to distinguish between campaign characteristics such as funding success and project orientation, which provides further valuable insights for prospective creators of campaigns, potential supporters as well as IS scholars. The objective of our study is to address the discussed gaps guided by the following research questions:

**RQ1:** What are the relative impacts of eWOM and prior-contribution behavior on the outcome of crowdfunding campaigns?

**RQ2:** How do these impacts vary for crowdfunding campaigns that reach their funding goal compared to those that do not?

**RQ3:** How do these impacts vary for crowdfunding campaigns in the distinct categories Cause, Creative, and Entrepreneurial?

To investigate the dynamic interplay between social buzz and contribution patterns over time, we have assembled daily project level data from Indiegogo.com, one of the largest reward-based crowdfunding platforms. Our social buzz measures were collected from Twitter and Facebook, the biggest unidirectional...
and bidirectional social networks on the web. Our empirical analysis is conducted using the panel vector autoregression (PVAR) approach (Dewan and Ramaprasad 2014).

Our study offers useful contributions to research and practice. First, it is among the first large-scale empirical studies to capture both intra- and cross-platform information flows that operate through users’ contribution and sharing behaviors. In doing so, we are not only able to identify strong intra-platform feedback loops, but also observe cross-platform effects in the form of social buzz that play an important role in predicting the success of crowdfunding campaigns. Second, we were able to reveal an inverse relationship between eWOM and contribution behaviors on online platforms. While social buzz has a positive effect on project backing, the effect is negative in the reverse direction. Third, by examining how social buzz influences the outcome of crowdfunding campaigns, this study gives platform providers and project creators important insights into the critical role of social media within different project categories. More broadly, our study enriches social media and IS platform research by disentangling the interdependencies between quality signals within and across platforms.

**Theoretical Background**

**Contribution Behavior on Crowdfunding Platforms**

Crowdfunding builds on the concept of crowdsourcing, which at its core allows individuals or organizations to reach a monetary (project) goal by receiving small financial contributions from a large number of individuals instead of choosing the traditional approach and receiving large contributions from a small number of creditors. Crowdfunding enables project creators to collect contributions from a large number of project backers through an open call—mostly on the Internet (Schwienbacher and Larralde 2012). The reasons for project creators to choose crowdfunding are manifold and not limited to financial aspects. The success of platforms such as Kickstarter and Indiegogo has also made crowdfunding a tool that enables the creators of entrepreneurial, creative, or social projects to validate their ideas on a large scale through the outcome of their campaign. Thus, a successful campaign does not only enable the creators to finance their venture or project, but it also validates that there is a market for it. Furthermore, the campaigns themselves can also have a certain marketing effect for the respective project (Burtch et al. 2013; Mollick 2014; Shane and Cable 2002).

On the other hand, we also see a variety of incentives for backers to “pledge” for a certain crowdfunding campaign. These incentives mainly depend on the return the backers can expect from their contribution, which can either be material, idealistic, or philanthropic in nature (Ahlers et al. 2012). Most campaigns, for example, offer at least one option that allows a donation without a material return. In our study, we focus on reward-based crowdfunding, as it is by far the most popular concept of crowdfunding today, but so far little empirical research has been devoted to it (Mollick 2014). Compared to donations, rewards have an increased complexity and level of uncertainty, as there are a number of conditions that have to be met before backers can eventually receive the reward. A fundamental condition is that sufficient funds are raised within the pre-arranged campaign runtime. Even though project creators on Indiegogo receive funds regardless of whether the funding goal is reached, not collecting enough funds will make it difficult for most creators to implement their project ideas. Furthermore, the backer’s investment cannot be put on the same level with a purchase, since there is usually no legal obligation for the project creator to produce and deliver the reward to the backer (Mollick 2014). The dynamics of crowdfunding are thus somewhat different from those in a traditional e-commerce setting between a seller and a buyer. Backers act as patrons and customers at the same time (Agrawal et al. 2011) and thus have a certain interest in the success of the crowdfunding campaign. Furthermore, backers can be less certain that they will actually receive the return on their investment and they have less information about the object they are investing in compared to a regular buying situation, in which the product or service already exists and can be inspected thoroughly. The primary source of information for a potential backer is therefore the campaign description the creator has published on the platform. This description almost always includes a short video, showing the creator, possibly some sort of prototype, the finished product or other important aspects of the campaign. Even though this content allows the backer to develop an attitude towards the campaign and the rewards comprised, this attitude is potentially biased due to the fact that all information stems from a single source. Consequently, rewards of crowdfunding campaigns can be seen as experience goods, whose value can only be ascertained by consuming them after the campaign has
ended, rather than search goods, whose characteristics and features can easily be evaluated prior to purchase (Nelson 1970). The quality of the reward thus remains relatively vague at the time the backer decides whether or not to pledge for a specific campaign. We therefore argue that other evidence for the trustworthiness and quality of a campaign becomes increasingly important for the potential backer’s evaluation. More specifically, we distinguish between two potential sources of information, namely, eWOM in the form of shares and tweets the campaign receives on Facebook and Twitter, and prior-contribution behavior in the form of the total number of backers.

**Electronic Word-of-Mouth (eWOM)**

Word-of-Mouth (WOM) is informal interpersonal communication between not commercially affiliated consumers about commercial content such as brands, products, or services (Arndt 1967; Bone 1995). Previous research found a significant influence of WOM on consumers’ information search, evaluation, and decision-making (e.g., Engel et al. 1969; Lynn 1987; Richins and Root-Shaffer 1988), as it “influences attitudes during the pre-choice evaluation of alternative service providers” (Buttle 1998). Furthermore, it has been shown that WOM can be more relevant than traditional marketing channels, such as advertising, in raising the awareness for innovation and in convincing the receiver to try out new products (Buttle 1998). WOM referrals have also been shown to have significantly longer carry-over effects than traditional marketing actions (Trusov et al. 2009), and a single WOM message can potentially influence a multitude of receivers (Lau and Ng 2001). One of the main reasons for the success of WOM is the increased perceived reliability, credibility, and trustworthiness compared to communication initiated by organizations themselves (Arndt 1967; Brown et al. 2007).

The advent of the Internet has drastically increased consumers’ options for exchanging opinions about products and services and offers them a large array of possibilities to engage in a specific form of WOM called electronic Word-of-Mouth (eWOM). While traditional (offline) WOM allows the consumer to evaluate and share opinions, eWOM also allows them to share and consume digital products at the same time. Still, it has been argued that the consumer motives that have been identified as being relevant for traditional WOM are also expected to be relevant for eWOM (Hennig-Thurau et al. 2004). According to Hennig-Thurau et al. (2004) eWOM is “any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet”. The opportunities that are available for consumers to share their opinion, preferences, or experiences online are manifold and a multitude of possible channels such as product review websites, blogs, online communities, and social networking websites are available. Due to their constant presence and accessibility, social networking websites such as Twitter and Facebook in particular have been used to generate enormous amounts of eWOM messages.

The receiver’s response to an eWOM message received via these channels depends on two sequential cognitive processes, namely, awareness and persuasiveness. The awareness effect can be explained by the sheer volume of eWOM, making it more likely for a receiver to be informed about the content (Godes and Mayzlin 2004; Liu 2006). Only after the receiver is aware of the content, does a cognitive process start, evaluating the message’s credibility by examining the message’s valence and the receiver’s social ties with the sender. Previous research has found that tie strength, homophily, and source credibility in particular affect the persuasiveness of eWOM messages (Brown et al. 2007; Chu and Kim 2011). Tie strength can help to encourage eWOM, as individuals in strong tie relationships tend to interact more frequently, exchange more information, and have a greater impact on the recuperative behavior, compared to those in a weak tie relationship (Brown et al. 2007; Brown and Reingen 1987). Homophily explains group composition in terms of the similarity of members’ characteristics (Brown et al. 2007), while source credibility is defined as the perceived competence of the source. Compared to traditional WOM, which is based on face-to-face transmission, tie strength, homophily, and source credibility may be more difficult to ascertain online (Brown et al. 2007).

In the context of crowdfunding, eWOM is likely to be of great importance for the success of a crowdfunding campaign, as it raises awareness for the project without requiring financial investments, and can be central in persuading potential backers to invest. Without eWOM, the campaign description remains the central source of information for the potential backer, who might be uncertain about the actual utility of the proposed project. While the total number of previous backers enables potential backers to infer the success of the campaign directly, it does not offer any information about the potential...
backer’s strength of relationship with the previous backers. Consequently, for those individuals who take into account their social network when making an investment, it might be more appropriate to use eWOM for decision support.

Although there is a growing body of literature on crowdfunding, the role of popularity information, eWOM, and especially the interplay among the different salient indicators remains largely unexplored in the context of crowdfunding. Thus far, crowdfunding itself has mainly attracted academics from disciplines such as finance and entrepreneurship (e.g., Belleflamme et al. 2013; Mollick 2014; Schwienbacher and Larralde 2012). A notable exception in the information systems (IS) literature is the empirical examination of social influences of prior-contribution behavior by Burtch et al. (2013). However, they examine reinforcement and substitution effects of prior contribution and do not take into account the influence of social buzz surrounding the campaign. Furthermore, their work is based on a crowdfunding market focused on public goods (donation-based crowdfunding), and thus the applicability to reward-based crowdfunding markets is limited. We therefore intend to advance the current literature by examining the dynamic effects that popularity information and social buzz have on the outcome of campaigns in reward-based crowdfunding markets.

**Research Model and Hypotheses Development**

In this section, we develop the theoretical rationale for our proposed research model. As shown in Figure 1, H1 and H3 focus on intra-platform effects, while H2 and H4 address cross-platform effects between social media and crowdfunding platforms and vice versa. We derive the first sets of hypotheses, H1 and H2, based on theory related to eWOM effectiveness in social media. We then develop H3 and H4, which are focused on the impact of prior contribution on future-contribution behavior and eWOM.

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<th>eWOM Effectiveness in Social Media</th>
<th>Informational Cascades</th>
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**Figure 1. Research Model**

**eWOM Effectiveness in Social Media**

Once a receiver becomes aware of an eWOM message via social media, its persuasiveness is evaluated based on its valance and the receiver’s social ties with the sender (Brown and Reingen 1987; Liu 2006). First, in the context of crowdfunding, the majority of eWOM messages can be expected to have a positive valence, as sharing a campaign via social media creates higher visibility for the campaign in any case. Messages with a negative sentiment will be rare, as consumers could not have had negative experiences with the offered product or service during the campaign runtime. Besides, as most investments in crowdfunding campaigns will be made based on hedonic rather than utilitarian motives, eWOM messages with a negative sentiment will be less likely to have an impact on the receiver anyway (Sen and Lerman 2007). Second, social networking websites such as Facebook and Twitter allow the receivers of eWOM messages to evaluate tie strength, homophily, and source credibility easily because this information can be conveniently accessed, making social networking sites an ideal vehicle for eWOM (Chu and Kim 2011). Consequently, eWOM messages received via Facebook and Twitter can be expected to be credible signals for the receiver. However, receiving a persuasive message may not necessarily coincide with an actual
response by the receiver. The effectiveness of eWOM describes the ability of eWOM messages to influence the receivers’ behaviors, e.g. in terms of purchase intention.

In this study, we distinguish two outcomes of effective eWOM, namely, the retransmission of a message related to a specific crowdfunding campaign in the receiver’s own network and the receiver’s financial investment in the respective crowdfunding campaign. We expect these two outcomes to be sequential in their timing and to differ in their magnitude, due to the different motives and risks associated with them, which will be discussed in the following. After receiving a message via Facebook or Twitter, the receiver evaluates whether to retransmit it or not. Generally, consumers tend to share eWOM messages in their own social network before an actual purchase for two important reasons. First, for self-representation or self-enhancement purposes (Wojnicki and Godes 2008), where content is shared by consumers because it may reflect favorably on them as a sender (Berger and Milkman 2012). Crowdfunding projects are most often technically innovative, socially responsible, or very creative and thus are ideal to reflect positively on the sender when shared via social media. Second, since a high perceived risk when making purchase or investment decisions leads to more extensive information gathering (Gemünden 1985), consumers tend to seek peer evaluation in situations of uncertainty by sharing specific content and evaluating the responses. Uncertainty is further increased, when consumers cannot try out products before making purchases (Benlian and Hess 2011). This is also consistent with the findings of King and Balasubramanian (1994), showing that other-based preference formation is particularly important for experience goods (Dewan and Ramaprasad 2014).

As mentioned, evaluating the actual utility of crowdfunding campaigns is difficult for potential investors due to the limited information provided in the campaign description, making peer evaluation a vital component for the decision-making of a potential backer. Therefore, both consumer motives for sharing and retransmitting messages can be expected to be critical for the diffusion of eWOM surrounding specific campaigns. Consequently, since it has been shown that a single eWOM message can potentially influence a multitude of receivers (Lau and Ng 2001), we expect that a positive shock, meaning an increase, in the number of shares on Facebook or tweets on Twitter will generate additional eWOM on the respective platform, creating intra-platform effects in the form of positive feedback loops:

H1a: A positive shock in the number of shares a specific crowdfunding campaign receives on Facebook will lead to additional Facebook shares for the respective campaign in the next period.

H1b: A positive shock in the number of tweets a specific crowdfunding campaign receives on Twitter will lead to additional tweets for the respective campaign in the next period.

Previous research has highlighted the importance of positive WOM in the diffusion of new products (e.g., Arndt 1967; Mahajan et al. 1984). Specifically, it has been argued that with higher perceived risk associated with the early adoption of new products, consumers tend to rely more on WOM, as it is perceived as more reliable, credible, and trustworthy compared to communication initiated by organizations themselves (Arndt 1967; Brown et al. 2007). Crowdfunding is different from a regular buying situation, as the investment is often required without an existing product or service, further increasing perceived risk and ultimately the importance of eWOM messages. Consequently, consumer motives that have been identified in previous research as being relevant for facilitating the investment decisions of consumers based on eWOM (e.g., Dhar and Chang 2009; Liu 2006) may not necessarily apply in the context of crowdfunding.

We argue that, due to the innovativeness of crowdfunding projects, potential backers will not actively search for certain campaigns, but will rather “stumble upon” them when using social media. In this context, weak ties have been shown to have an important bridging function that allows information to disseminate and spread among distinct groups (Chu and Kim 2011; Granovetter 1973). Even though weak ties are essential in the process of finding new content, potential backers will be reluctant to rely on them for decision support. Strong ties, on the other hand, constitute a firmer and closer relationship and are thus equally important, as they provide a substantive decision support. Since Twitter is modeled as a directed graph, meaning that the connections among the members of the network are unidirectional (weak ties), whereas Facebook is modeled as an undirected graph with bidirectional connections (strong ties), differences in their effectiveness are to be expected. Therefore, eWOM volume on both Facebook and Twitter should influence the receiver’s investment decisions in a positive way:
H2a: A positive shock in the number of shares for a specific campaign on Facebook will attract additional backers for the respective campaign in the next period.

H2b: A positive shock in the number of tweets for a specific campaign on Twitter will attract additional backers for the respective campaign in the next period.

**Informational Cascades on Crowdfunding Platforms**

Informational cascades offer an information-based explanation for herd behavior and occur when individuals who face a certain decision choose to follow the actions of others instead of taking a decision based on their own private information (Bikhchandani et al. 1992; Bikhchandani et al. 1998). Such a situation may arise when the individual facing the decision has imperfect knowledge of the product’s quality and thus infers its utility by observing the actions of predecessors (Duan et al. 2009). Consequently, informational cascades emerge in situations of sequential decision-making and if the actions (but not the decision-making processes) of other individuals are observable (Huck and Oechssler 2000). These situations may arise frequently on crowdfunding platforms, as the only available source of information is the campaign description published by the campaign creator, which might be limited in scope, imperfect, or biased. Uncertainty is further increased due to a lack of face-to-face interaction with the creator or the possibility to trial the product or service before investing (Benlian et al. 2012). Prospective backers thus infer the product’s utility by observing prior-contribution behavior, for example based on popularity information displayed on the platform in form of the total number of previous backers. Popularity information has been found to have a positive influence on subsequent sales performance, e.g. in the context of online software adoption (Duan et al. 2009).

Previous research on the effects of prior-contribution behavior on the decision-making of potential backers has found that in donation-based crowdfunding markets, the “marginal utility contributors gain from giving to a particular project is diminished” through the contribution of other backers (Burtch et al. 2013). The reason is that potential backers see less “need” to contribute as others have already supported the campaign, leading to negative downward informational cascades and ultimately a stagnation of contribution. Also, projects on Indiegogo sometimes have a limited number of material rewards available, which can be sold out before the funding period is over. Running out of these particular attractive rewards might lead to a stagnation of contributions for already successful campaigns.

On the other hand, in equity- and lending-based crowdfunding markets, backers rather invest in projects that already have a lot of support, which signals a superior quality. Consequently, supporting an already successful project becomes a “rational” decision for backers in order to reduce their own risk (Herzenstein et al. 2011; Zhang and Liu 2012). Hence, already popular campaigns receive an additional popularity boost, leading to positive upward informational cascades. To our best knowledge, this (intra-platform) effect has not yet been empirically investigated in reward-based crowdfunding markets, and it remains unclear whether one can expect positive upward or negative downward informational cascades—or neither. However, we hypothesize that the intentions of backers in reward-based crowdfunding markets are similar to those in equity- and lending-based crowdfunding markets, as receiving a reward can be seen as the primary objective in all three markets. The risk of not receiving a reward for the investment might be rather high, as the project creators do not have to choose the “All or Nothing” model where the funds invested in an unsuccessful project are reimbursed to the investor. Consequently, creators of campaigns that do not reach the designated funding goal will still receive the funds invested in the campaign, but might be unable to deliver the rewards comprised to the backers due to the lack of funding. Thus, backers try to minimize their risk of pledging without receiving a reward and invest in campaigns that are already successful in terms of the number of backers, leading to a reinforcement effect on the crowdfunding platform. We thus expect to identify informational cascades and propose that:

H3: A positive shock in the number of backers supporting a specific crowdfunding campaign will attract additional backers for the respective campaign in the next period.

Similarly, backers try to further increase the likelihood of the campaign becoming successful after their investment in order to secure their reward. As a result, it becomes rational for them to create additional eWOM by spreading the campaign in their respective network to attract other backers and therefore reduce their own investment risk. Thus, even though backers of a specific campaign will not receive their reward until after the campaign has ended, the perceived personal relevance of the project and the reward...
to the backer (Dholakia 1997), which is referred to as product involvement, will already be rather high due to anticipation and higher perceived risk when making the investment. This product involvement has been identified as a central driver of WOM (Dichter 1966; Sundaram et al. 1998), as recommending products and services to others reduces the tension caused by the consumption experience (Dichter 1966). Finally, for self-enhancement purposes, actual and potential backers of a specific campaign will rather choose to share a project in their own network that has already attracted plenty of backers, as popular and positive content reflects more favorable on the sender (Berger and Milkman 2012). We therefore expect to see positive cross-platform effects from the crowdfunding platform to social media:

**H4a**: A positive shock in the number of backers supporting a specific crowdfunding campaign will lead to additional shares for the respective campaign on Facebook in the next period.

**H4b**: A positive shock in the number of backers supporting a specific crowdfunding campaign will lead to additional tweets for the respective campaign on Twitter in the next period.

### Research Methodology

#### Model and Variables

As we examine the interactions between social buzz and contribution behavior, we first conduct Granger causality tests to examine the potential endogeneity between the dyads of our key variables, backers, Facebook shares, and tweets (Granger 1969). Next, we employ a panel vector autoregressive approach using daily project level data (Holtz-Eakin et al. 1988). Panel vector autoregressive models are used to capture interdependencies among multiple time series and are suitable for studying the relationships between a system of interdependent variables without imposing ad hoc model restrictions, including exogeneity of some of the variables, which other econometric model techniques require (Adomavicius et al. 2012). Vector autoregressive models have, for example, proven to be especially useful for describing the dynamic behavior of economic and financial time series and forecasting (Zivot and Wang 2007). In marketing research, PVAR modeling has for example been used to analyze the effects of marketing investments on sales performance (Dekimpe and Hanssens 1995) or to investigate the relationship between an artist’s broadcast behavior in social media and sales performance (Chen et al. 2011).

The main challenges of our model setup are the simultaneous mutual influences of the different variables of interest, namely, the number of backers and the number of social media shares on Facebook and Twitter. Consistent with Dewan and Ramaprasad (2014), we distinguish the mutual effects by focusing on the orthogonalized impulse-response functions, which show the response of one variable of interest in the next period (e.g. Facebook shares) to an orthogonal shock of one standard deviation in another variable of interest in the current period (e.g. number of backers). By orthogonalizing the response, we are able to identify the effect of one shock at a time, while holding other shocks constant. This technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for unobserved individual heterogeneity (Love and Zicchino 2006). When applying the VAR procedure to panel data, a certain restriction must be imposed. The underlying structure must be the same for each cross-sectional unit. Since this constraint is likely to be violated in practice, usually fixed effects are introduced. As the fixed effects are correlated with the regressors due to the lags of the dependent variables, we use forward mean-differencing, also referred to as the “Helmert procedure” (Arellano and Bover 1995). This procedure removes only the forward mean and preserves the orthogonality between transformed variables and lagged regressors. We can then use lagged regressors as instruments and estimate the coefficients by a generalized method of moments (GMM) (Love and Zicchino 2006). Our PVAR Model is then specified for each project as,

\[
\begin{bmatrix}
    \text{backers}_t \\
    \text{facebookshares}_t \\
    \text{tweets}_t
\end{bmatrix} = \sum_{j=1}^{J} \begin{bmatrix}
    \beta_{11}^{t-j} & \beta_{12}^{t-j} & \beta_{13}^{t-j} \\
    \beta_{21}^{t-j} & \beta_{22}^{t-j} & \beta_{23}^{t-j} \\
    \beta_{31}^{t-j} & \beta_{32}^{t-j} & \beta_{33}^{t-j}
\end{bmatrix} \begin{bmatrix}
    \text{backers}_{t-j} \\
    \text{facebookshares}_{t-j} \\
    \text{tweets}_{t-j}
\end{bmatrix} + \begin{bmatrix}
    \varepsilon_{\text{back} t} \\
    \varepsilon_{\text{fb} t} \\
    \varepsilon_{\text{tw} t}
\end{bmatrix}
\]

where backers, facebookshares, and tweets denote daily project funders, shares on Facebook and tweets on Twitter. The number of backers of a project (backers) is our proxy for the project’s commercial success, while shares on Facebook and tweets on Twitter represent eWOM. Even though it might be argued that the amount of funding a project received is a more suitable indicator of its success, we...
deliberately chose the number of backers as our dependent variable due to the following reasons. First and foremost, our intention was to examine the impact the behavior of individual crowdfunding users has in the overall system, which is also reflected in our theoretical approach. Using the funding amount instead of backers would, in our opinion, not correctly reflect user behavior and the dynamic relationship. Second, in the long term, knowing how many individuals are interested in a certain crowdfunding project might be more relevant to the creator of the project than reaching a short-term financial goal. Finally, the correlation between backers and funding amount is extremely high, allowing to infer the campaign’s success from the number of backers.

\( J \) is the order of the model, which can be determined using Akaike’s information criterion (AIC). Thus, in the project success analysis, today’s backers are a function of past shares on Facebook, past tweets on Twitter, past backers, and an error term. In the PVAR Model, the coefficients represent the relationship between the lagged values of each variable and the variable on the left-hand side of the equation. The appropriate order, or lag length, \( j \) was determined by using the AIC, following the standard approach in VAR literature (Holtz-Eakin et al. 1988; Love and Zicchino 2006). Specifically, we had to calculate the AIC for each cross-section and take the modal value of the optimal lag among all cross sections, following Dewan and Ramaprasad (2014). To analyze the impulse-response functions, an estimation of confidence intervals is required. Since we construct the matrix of the impulse-response function from the estimated VAR coefficients, their standard errors must be taken into account. We therefore calculate standard errors of the impulse-response function and generate confidence intervals with Monte-Carlo simulations. In practice, we randomly generate a draw of coefficients of model (1) using the estimated coefficients and their variance-covariance matrix and re-calculate the impulse-responses. We repeat this procedure 1,000 times (we also ran the calculation with a larger number of repetitions and obtained similar results). Finally, we also calculate variance decompositions, which show the percentage of the variation in one variable that is explained by the shock of another variable.

**Dataset**

Our cross-section project-level data was collected from Indiegogo.com, which is among the largest and most prominent crowdfunding platforms on the web. Specifically, the data covers the period from November 15th 2013 to March 24th 2014, resulting in approximately 186,500 data points. Data on every project available was gathered automatically with a self-developed web crawler to retrieve time-series data of all projects on the website in a daily routine. Besides the dependent variables of project backers, we gathered additional information on every project to create meaningful subsamples of our dataset. The categorical indicators of each project primarily include the general orientation of the campaign (Creative, Social, or Entrepreneurial), and we further marked every project as successful that reached or exceeded its funding goal. We choose this threshold, as projects tend to either fail by a large margin or surpass their funding goal (Mollick 2014).

<table>
<thead>
<tr>
<th></th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
</tr>
<tr>
<td>Backers</td>
<td>46.36 (289.35)</td>
</tr>
<tr>
<td>Facebook (#Shares)</td>
<td>245.58 (443.38)</td>
</tr>
<tr>
<td>Twitter (#Tweets)</td>
<td>26.59 (151.85)</td>
</tr>
<tr>
<td>Received Funding</td>
<td>3,465$ (13,696$)</td>
</tr>
<tr>
<td>N (Projects)</td>
<td>6,340</td>
</tr>
</tbody>
</table>

**Table 1. Summary Statistics**
As mentioned earlier, for our study, we consider two types of social buzz: shares on Facebook and tweets on Twitter. Based on the application programming interfaces (API) of Facebook and Twitter we collected the daily data for the number of shares and tweets a specific campaign had received in the last 24 hours to construct our eWOM measurements. In order to quantify the volume of social buzz correctly, we only considered shares and tweets that contained a direct hyperlink to the crowdfunding campaign on Indiegogo. To account for potential deadline and commiseration effects, we only analyzed projects that were covered during their complete lifecycle (Kuppuswamy and Bayus 2014). Furthermore, campaigns that showed unnatural peaks in shares or tweets on a single day had to be excluded. Even though natural eWOM peaks can be expected when a project 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 shares and tweets over time. On the contrary, unnatural peaks do not show these subsequent effects and therefore imply fraudulent actions such as purchasing shares and tweets, which would have distorted the results. These unnatural peaks were therefore identified if the number of additional shares or tweets exceeded the threefold standard deviation, were higher than 500, and occurred on a single day.

We expect circularity effects to be present only in flourishing campaigns and therefore split our dataset in winning and losing campaigns. A split-sample PVAR analysis for each project topic was then only performed for successful campaigns. This results in a dataset including 6,340 projects, of which 27.7% were successful, had an average funding duration of 29 days, and approximately 186,500 observations. Summary statistics are presented in Table 1 for the full dataset and each subsample.

Results

To conduct both Granger Causality as well as PVAR analysis, the variables in question must be stationary. We therefore employ a Phillips-Perron unit root test for panel data (Phillips and Perron 1988). Results are presented in Table 2 and indicate that all of the variables are indeed stationary.

<table>
<thead>
<tr>
<th>Table 2. Phillips-Perron Unit Root Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Backers</td>
</tr>
<tr>
<td>Facebook (#Shares)</td>
</tr>
<tr>
<td>Twitter (#Tweets)</td>
</tr>
</tbody>
</table>

Note: Phillips-Perron unit-root is appropriate as it allows unbalanced data. The null hypothesis that the panels contain unit roots is rejected for all variables.

Next, we conducted the Granger causality test to validate our PVAR approach. Table 3 presents the results that strongly support our research approach by giving clear evidence of bidirectional causality in each pair of dependent variables. We can therefore analyze our variables as a full dynamic system through PVAR analysis (Trusov et al. 2009).

<table>
<thead>
<tr>
<th>Table 3. Granger Causality Tests</th>
</tr>
</thead>
<tbody>
<tr>
<td>Backers</td>
</tr>
<tr>
<td>Backers</td>
</tr>
<tr>
<td>Facebook (#Shares)</td>
</tr>
<tr>
<td>Twitter (#Tweets)</td>
</tr>
</tbody>
</table>

Note: The results reported are CHI² statistics with p-values in parentheses. Granger causality tests are performed with 1 lag for consistency with the PVAR Models (as selected by AIC).
Main Results

To test our research hypotheses, we estimate the coefficients of the system given in (1). Results from the PVAR analysis for all models, including the split-sample analysis, are reported in Table 4. We first examine the results for the complete model and all hypotheses before discussing the details of the split-sample analysis in the subsequent section. Our first hypotheses H1a and H1b stated that, for the total model, a positive shock in social buzz, measured in shares and tweets within a social network, leads to additional shares or tweets within the respective platform. We find strong support for these two intra-platform hypotheses, implying a strong reinforcement effect of social buzz within each social network platform. Additionally, we can observe higher coefficients for the bidirectional network (Facebook) compared to the unidirectional counterpart (Twitter). This implies, unsurprisingly, that users rather share content and seek peer evaluation from a bidirectional network with generally stronger ties compared to a more impersonal network such as Twitter.

For our second set of hypotheses, H2a and H2b, we seized the opportunity to shed light on the direct cross-platform effects of social buzz on subsequent contribution behavior by additional backers. In our model, we are able to estimate the effect of yesterday’s social buzz on Twitter and Facebook on today’s number of backers of a campaign. Results show that there is a significant and positive effect of yesterday’s Facebook shares on today’s backers. Surprisingly, we see no effect for tweets in our model. Thus, results show strong support for H2a while H2b has to be rejected. This again gives us further reason to believe that users trust recommendations from their personal and bidirectional network more than the rather impersonal investment suggestions from a unidirectional network. This emphasizes the importance of strong ties in the crowdfunding context. We checked for robustness of the effect, as the influence of Twitter might be mediated through Facebook shares, but cross-platform effects between Facebook and Twitter are virtually non-existent, as seen in Table 4.

Table 4. PVAR Results for Split-Sample Analysis

<table>
<thead>
<tr>
<th>Response to:</th>
<th>Response of dependent variable: Backers</th>
<th>Total</th>
<th>Winner</th>
<th>Loser</th>
<th>Winner: Creative</th>
<th>Winner: Social</th>
<th>Winner: Entrepreneurial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Backers₁₄</td>
<td>0.556***</td>
<td>0.514***</td>
<td>0.922***</td>
<td>0.484***</td>
<td>0.899***</td>
<td>0.892***</td>
<td></td>
</tr>
<tr>
<td>Facebook₁</td>
<td>0.052***</td>
<td>0.094***</td>
<td>0.001</td>
<td>0.125***</td>
<td>0.002</td>
<td>0.015***</td>
<td></td>
</tr>
<tr>
<td>Twitter₁</td>
<td>-0.002</td>
<td>-0.071*</td>
<td>0.001</td>
<td>-0.255***</td>
<td>0.001</td>
<td>-0.083***</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Response to:</th>
<th>Response of dependent variable: Facebook</th>
<th>Backers₁₄</th>
<th>-0.200***</th>
<th>-0.218***</th>
<th>-0.016</th>
<th>-0.243***</th>
<th>0.069</th>
<th>-0.053</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facebook₁</td>
<td>0.951***</td>
<td>0.968***</td>
<td>0.926***</td>
<td>0.997***</td>
<td>0.883***</td>
<td>0.950***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Twitter₁</td>
<td>0.002</td>
<td>-0.032</td>
<td>0.002</td>
<td>-0.114*</td>
<td>-0.025</td>
<td>-0.147*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Response to:</th>
<th>Response of dependent variable: Twitter</th>
<th>Backers₁₄</th>
<th>-0.053**</th>
<th>-0.048*</th>
<th>0.034***</th>
<th>-0.067***</th>
<th>0.197***</th>
<th>0.013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facebook₁</td>
<td>0.006*</td>
<td>0.001</td>
<td>0.001</td>
<td>0.016**</td>
<td>-0.066***</td>
<td>0.009*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Twitter₁</td>
<td>0.898***</td>
<td>0.855***</td>
<td>0.904***</td>
<td>0.906***</td>
<td>0.765***</td>
<td>0.753***</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: PVAR Model is estimated by GMM. Reported numbers show the coefficients of regressing the column variables on lags of the row variables. Heteroscedasticity adjusted t-statistics are in parentheses. ***, **, * denote significance at 0.1%, 1%, and 5% respectively.

Our third hypothesis was based on the theory of informational cascades, eWOM, and the assumption that backers try to minimize their risk of pledging without receiving a reward and invest in campaigns that are already successful in terms of the number of backers. We observe a strong positive response of the number of backers to a shock of their own lagged value. This positive and significant response supports the argument on positive upward informational cascades within platforms and suggests a strong self-reinforcement effect of popularity information for crowdfunding projects, in support of H3. Furthermore,
we see that each additional backer does not only support a project financially, but also increases its reputation, leading to a multiplying effect.

For our last set of hypotheses, H4a and H4b, we argued for a cross-platform reinforcement effect of additional backers in the current period leading to additional social buzz in the next period. In other words, we expect supporters of a project to spread their investment decision among their peers, as it reflects positively on them and creating additional social buzz should further secure their investment. Contrary to our expectations, results in Table 4 show the exact opposite response of Facebook shares and tweets to an increased number of backers in the preceding period. A possible explanation for this relation might be that users spread the information about a project mainly prior to the investment in order to receive feedback from their peers and are not inclined or permitted by the social network platform to share it twice. On the other hand, backers might simply discover the project via social media and do not see an incentive to spread it further, creating a possible crowding-out effect (Andreoni 1990; Roberts 1984), meaning that as the level of contributions rises, backers perceive the project to be sufficiently financed and therefore see no need to promote the project any further. Additionally, we observe ambiguous effects, as the coefficient for successful social projects is in fact positive for tweets, while it is negative for creative projects’ Facebook shares as well as Tweets. Following the argument from above, a possible crowding-out effect exists for creative projects, while social projects do not suffer from it. Moreover, these results suggest that backer seek feedback from their peers before supporting creative projects, while social and entrepreneurial campaigns do not require this evaluation process.

**Split-Sample Analysis**

Our analysis continues by exploring how the orientation and the success of the project are reflected in the relationship between backers’ contribution behavior and social buzz. Results from the split-sample analysis in Table 4 show interesting differences between the types of projects. First, we can see that the relationship regarding the effect of eWOM across platforms is virtually non-existent for projects that fail to reach their funding goal, while the reinforcement effect within a platform still holds regardless of the success. These results imply that for crowdfunding campaigns, social buzz can be a crucial success factor.

Looking at the split-sample on project topics, we see distinct differences. For instance, the reinforcement effect of prior-contribution behavior within the crowdfunding platform is much weaker for creative projects compared to social and entrepreneurial campaigns, while the social buzz effect from Facebook shares is significantly stronger. This result suggests that creative projects profit more from Facebook shares as a marketing tool, which is not surprising, as these projects often include films, music, and other forms of art which are popular, and consumers tend to share positive content for self-representation purposes (Wojnicki and Godes 2008). This is also reflected in the coefficients for the internal platform effect of Facebook shares, which is highest for creative projects and lowest for social projects, which are often related to negative environments or misfortunes. Presumably, users are reluctant to share these rather tragic or distressing campaigns. Furthermore, creative and entrepreneurial projects show a positive effect of Facebook shares on the number of backers in the following period. However, this effect does not show for social projects, suggesting a strong bystander effect, in which people in fact promote the project in their social network, but do not offer any financial aid. This result is consistent with classic literature on the bystander effect and public goods (Fischer et al. 2011).

Finally, we also present the results of a variance decomposition analysis in Table 5, which show the percentage of the variation in one variable that is explained by the shock of another variable, accumulated over time. The variance decomposition shows the magnitude of the total effect (Love and Zicchino 2006). Total effects accumulated over 4 weeks are reported, as longer and shorter time horizons produced equivalent results and the table corresponds to the calculated Impulse-Response Functions’ time frame. We only show results for backers as a dependent variable, as it is the most relevant variable in the context of crowdfunding. Results are in line with the insights from the PVAR estimation, showing that most of the variance within the dependent variable is explained by their own lags, suggesting a very strong feedback loop within the platform rather than across them and a stronger effect for Facebook shares compared to tweets from Twitter. Interestingly, the explanatory power of Facebook shares increases over time, particularly for winner campaigns, so that about 4 percent of the variance in backers is explained by Facebook shares after 7 days, and almost 10 percent after 28 days. By comparison, the explanatory power of tweets is very weak over time, if not nonexistent.
### Table 5. Variance Decomposition of Backers

<table>
<thead>
<tr>
<th>Days Ahead</th>
<th>Backers</th>
<th>Facebook</th>
<th>Twitter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full Dataset</td>
<td>Creative</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Days Ahead</td>
<td>Backers</td>
<td>Facebook</td>
</tr>
<tr>
<td>7</td>
<td>95.5%</td>
<td>4.5%</td>
<td>0%</td>
</tr>
<tr>
<td>14</td>
<td>92.1%</td>
<td>7.9%</td>
<td>0%</td>
</tr>
<tr>
<td>21</td>
<td>91.1%</td>
<td>8.9%</td>
<td>0%</td>
</tr>
<tr>
<td>28</td>
<td>90.7%</td>
<td>9.3%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>Winner</td>
<td>Social</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>95.6%</td>
<td>4.1%</td>
<td>0.3%</td>
</tr>
<tr>
<td>14</td>
<td>92.5%</td>
<td>7.1%</td>
<td>0.4%</td>
</tr>
<tr>
<td>21</td>
<td>91.4%</td>
<td>8.2%</td>
<td>0.4%</td>
</tr>
<tr>
<td>28</td>
<td>91.1%</td>
<td>8.5%</td>
<td>0.4%</td>
</tr>
<tr>
<td></td>
<td>Loser</td>
<td>Entrepreneurial</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>99.96%</td>
<td>0.03%</td>
<td>0.0%</td>
</tr>
<tr>
<td>14</td>
<td>99.9%</td>
<td>0.1%</td>
<td>0.0%</td>
</tr>
<tr>
<td>21</td>
<td>99.8%</td>
<td>0.2%</td>
<td>0.0%</td>
</tr>
<tr>
<td>28</td>
<td>99.7%</td>
<td>0.3%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

**Note:** Percent of variation in the backer variable explained by column variable (7, 14, 21, and 28 days ahead) for each subsample and main regression.

### Impulse Response Functions

We supplement regression estimates with an analysis of the corresponding impulse response functions for our basic model. Graphs of the impulse-response functions (IRFs) with 5% error bands and 28 periods as the time span generated by Monte-Carlo simulations are presented in Figure 2. IRFs allow us to illustrate a response of one dependent variable to one standard deviation shock in another dependent variable in the preceding period.

All responses, except the response of backers to a shock in tweets, are positive but vary in their significance and magnitude. We see that there is a strong immediate effect of $b_{acker_{t-1}}$ on $b_{acker_{t}}$, which attenuates rather quickly, while the response of $b_{acker_{t}}$ on a shock in $facebookshares_{t-1}$ is weaker and recedes more slowly. Overall, a shock in $tweets_{t-1}$ has virtually no effect on the other dependent variables, while shocks in $facebookshares_{t-1}$ appear to be effective for a longer period of time, and shocks in $b_{acker_{t-1}}$ are very powerful in the short run but also decline extremely fast.
Discussion

Our analysis of the dynamic relationship between social media channels and contribution behaviors revealed interesting and surprising results on several levels. Corresponding to our first research question, we were able to identify an inversed relationship between social buzz and project support, revealing a positive impact of social buzz on subsequent campaign support in contrast to a negative impact of campaign support on consecutive social buzz. This indicates that potential backers learn about projects from their social network and demand feedback from their peers before investing in a project. However, backers are subsequently not willing or able to share the campaign with their respective social network. Furthermore, these effects are more definite for the bidirectional social network Facebook, compared to the unidirectional network Twitter, where the effects were weak, if not absent.

For our second research question, we were able to show the critical role of social buzz for the outcome of reward-based crowdfunding campaigns. As shown in our split-sample analysis, cross-platform effects of eWOM are virtually non-existent for campaigns that fail to reach the desired funding goal, while successful creators are able to capitalize on the information distribution in social media. Even more interestingly, the relative predictive power of Facebook shares increases over time, especially for winning campaigns, indicating that social media buzz is a crucial discriminating factor for the success of crowdfunding campaigns. To answer our third research question, we extended our sample-split analysis to a project’s general orientation, and we were able to identify reinforcement effects of social buzz for creative and entrepreneurial projects, as well as significant bystander effects for social campaigns.

Finally, we were able to illustrate intra- and cross-platform effects over time by analyzing the shocks triggered by social buzz and contribution behavior. We thereby could reveal that the impact of a positive shock in backers abates relatively fast, while the effects of a positive shock in social buzz decrease at a lower rate. However, the effect of social buzz is present and significant for a much longer time span.
**Theoretical Contributions**

Our study makes two unique theoretical contributions. First, to the best of our knowledge, this is one of the first studies to capture both intra- and cross-platform information flows that operate through users’ contribution and sharing behaviors. In doing so, we were able to identify strong intra-platform feedback loops, but also witnessed that cross-platform effects in the form of social buzz can play an important role in predicting success of crowdfunding campaigns. Second, we were able to reveal a novel aspect of the relationship between eWOM and contribution behavior on online platforms. More specifically, we found evidence that after funding a project, supporters perceive the project to be sufficiently financed and therefore see no need to promote the campaign any further in their social network, creating an inverse relationship between contribution behavior and eWOM. These reciprocal effects not only manifest themselves on an aggregate macro-level (i.e., platform) but also on a finer-grained micro-level (i.e., project categories). Our study thus contributes to social media research by advancing our understanding of the effectiveness, diffusion patterns, and context dependency of eWOM. We further believe that our insights are not limited to the crowdfunding context, as informational cascades and social buzz are an ubiquitous phenomenon within and between online platforms (Benlian et al. 2015). Overall, these insights should thus also make meaningful contributions to IS platform research.

**Practical Implications**

Our findings do not only enrich streams of research related to the dynamics of crowdfunding platforms and the effects of eWOM on performance measures; we also see a variety of practical implications that should be considered, in particular by the providers of crowdfunding platforms and creators of crowdfunding campaigns. First, creators should be aware that social buzz can be a decisive factor for their campaign’s success, as backers often learn about the projects in their social networks and are generally willing to spread the word about their investment. Therefore, creators should be ready to engage in social media marketing and encourage backers to further share the campaign with their peers. Still, this multiplying effect strongly varies between the project’s orientations. As we saw from our analysis, social projects are shared significantly less via social media, whereas creative projects receive much more attention. Second, project creators should focus on favorable aspects of the projects in their campaign descriptions in order to reflect positively on the messenger and encourage additional dissemination throughout the network. Third, as platform providers directly profit from successful projects, they should encourage creators as well as backers to share the projects with their respective social networks. Possible design improvements may include more prominently displayed share buttons and notifications, highlighting the beneficial effects of sharing a project in social networks after backing it. Fourth, our results highlight the predominance of Facebook compared to Twitter when it comes to eWOM effectiveness. We believe this can be partly attributed to the strict word limit on Twitter, the more elaborate display possibilities on Facebook and the generally stronger ties on Facebook, where source credibility tends to be higher. These findings should be taken into account for the allocation of marketing resources. Finally, understanding users’ sharing behavior and its impact on subsequent product or campaign performance are highly important for today’s businesses. We therefore believe that our insights on whether and why information spreads within or between platforms and how it ultimately affects consumer decision-making can be crucial for a firm’s digital strategy.

**Limitations, Future Research, and Conclusion**

While our study provides important contributions to both research and practice in the context of crowdfunding and the effects of eWOM, we acknowledge certain limitations that have to be considered when interpreting the results and implications. First, we were unable to take into account all different types of eWOM and have thus limited our analysis to messages spread via the two most prominent types of social media, namely Facebook and Twitter. Furthermore, due to the restrictions imposed by using Vector Auto Regression models we were unable to capture any non-linear relationships/growth rates. Second, we focused on the volume of eWOM rather than on its valence. However, we see little incentives for users of Twitter and Facebook to share a crowdfunding project to produce negative feedback and thus expected the majority of eWOM messages to be positive or neutral. Still, it might be of interest for future research to measure the impact of positive and negative eWOM separately, possibly by implementing semantic eWOM analysis tools. Third, we did not differentiate between the sources of eWOM on Facebook...
and Twitter. Potentially, the characteristics of the information provider might reveal additional insights. These characteristics could include the number of friends/followers, commercial or private accounts, and expertise. Fourth, since we derived our insights from just one crowdfunding platform, researchers should be cautious when generalizing these findings to other crowdfunding and different online platforms, as they potentially differ from Indiegogo in funding mechanisms and project orientation. Nevertheless, as Indiegogo is one of the best established and widely used crowdfunding platforms worldwide, the patterns of results identified in this study should also have valuable theoretical and practical implications for other platforms. Fifth, possible seasonality effects were not taken into account in our analysis. Yet, we do not regard this limitation as critical, as we did not observe any irregularities on Christmas or any other holiday season during the observation period. Finally, our study focuses solely on short-term dynamics, and the long-term interplay might differ from our insights. Overcoming these limitations might provide fruitful directions for future research in these fields. Promising other future research fields on the project level in a crowdfunding setting are comparisons of different lifecycle statuses, project sizes, reward structures, and individual investment amounts. Promising research avenues for eWOM effectiveness in this context might be the campaign complexity, sharing mechanisms, the individual reach of eWOM messages, and sender characteristics.

Overall, this study is an initial step towards understanding the dynamic interplay between eWOM, prior-contribution behavior, and actual contribution patterns operating within and across online platforms. We hope that our results provide impetus for further analysis of the intra- and cross-platform interdependencies between social buzz and contribution behaviors, and give actionable recommendations to platform providers and project creators in the crowdfunding context.

References


