Crowdfunding: Platform Dynamics under Asymmetric Information

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Abstract

Platform ecosystems are a growing trend in various industries and many companies that rely on this organizational structure have seen unprecedented growth rates in recent years. Compared to traditional service providers, platforms do not offer products or services directly to their customers, but almost exclusively through complementors who develop and deliver complementary content. Platforms therefore create value by enabling and coordinating interactions between the demand and the supply side. As these platforms are two-sided markets, they are characterized by distinct cross-side network effects, meaning that each side of the market derives externalities from the participation of the respective other group.

Crowdfunding platforms rely on this concept and facilitate transactions between individuals who seek funding for a specific project or venture and prospective investors. Crowdfunding platforms are, however, special as the transactions made via the platforms are particularly risky for end-users because of a high level of information asymmetry existing between the market sides. Though a certain level of information asymmetry exists between the distinct market sides in every two-sided market, a number of factors amplify this problem in the crowdfunding context. For instance, there is usually little to no publicly available information such as customer reviews to evaluate the investments ex-ante. The creators of crowdfunding campaigns are therefore able to overstate quality or withhold information as they control the flow of information towards potential investors. Furthermore, many of the projects that are published on crowdfunding platforms are still in their infancy, making it difficult to accurately predict project outcomes. Compared to other types of two-sided markets, the issue of information asymmetry is also more difficult to resolve in crowdfunding because mechanisms such as reputation systems that are frequently applied in other contexts to mitigate this issue are less relevant on crowdfunding platforms. The actual utility of crowdfunding projects is therefore difficult to ascertain at the time the investment decision has to be made and dynamics of crowdfunding are thus different from those in other platform settings. Many open questions still remain with respect to the optimal market design of crowdfunding platforms in order to mitigate information asymmetries.

Against this backdrop, four research studies have been conducted to investigate how the behaviors and actions of the distinct groups of market participants (i.e., platform provider, project creators, backers) influence the decision-making of potential backers on crowdfunding platforms. The first study is concerned with the effects actions taken by platform providers can have for the decision-making of backers. More specifically, it is examined how relaxing the input control for crowdfunding projects on Kickstarter affected the decision-making of backers. The second and third study are concerned with the role of social buzz and contribution behavior by previous backers. While the second study is focused on the dynamic interplay of social buzz, prior-contribution behavior, and the respective effects on backer decision-making, the third study describes the repercussions of non-genuine social media likes for project creators. The final study is focused on the influence project creators can have on backers by signaling certain personality traits through their project description and video.

Overall, this thesis highlights that, as a result of the high level of information asymmetry on crowdfunding platforms, prospective backers seek alternative information and signals to use for decision support in the face of uncertainty. Platform providers and project creators may use the results to better understand how and why certain actions or behaviors of market participants on crowdfunding platforms affect the decision-making of prospective backers. The findings may therefore help platform providers to optimize the market design of crowdfunding platforms in order to avoid information-related market failure in the long term.

Zusammenfassung

In den vergangenen Jahren haben Plattform-Ökosysteme in den verschiedensten Branchen stetig an Bedeutung gewonnen und viele Unternehmen konnten durch diese Organisationsstruktur enorme Wachstumsraten erreichen. Plattformen unterscheiden sich von anderen Unternehmen dadurch, dass sie dem Kunden Produkte oder Dienstleistungen nicht direkt, sondern fast ausschließlich über die sogenannten Komplementäre anbieten. Die Hauptaufgabe der Plattformen ist dabei, die Interaktionen und Transaktionen zwischen der Nachfrage- und der Angebotsseite des Marktes zu koordinieren. Da diese Plattformen zweiseitige Märkte sind, existieren indirekte Netzwerkeffekte zwischen den Marktseiten, sodass diese sich gegenseitig in ihrem Nachfrageverhalten beeinflussen.

Crowdfunding-Plattformen bauen auf dieses Konzept auf und ermöglichen Transaktionen zwischen Personen, die für die Finanzierung eines bestimmten Projektes oder einer Geschäftsidee Investoren suchen. Crowdfunding-Plattformen unterscheiden sich jedoch von anderen Plattformen, da die Transaktionen für die Personen auf der Nachfrageseite des Marktes aufgrund hoher Informationsasymmetrien besonders riskant sind. Obwohl Informationsasymmetrien in den meisten zweiseitigen Märkten die Transaktionen zwischen den Marktseiten beeinflussen, ist dieses Problem im Crowdfunding-Kontext durch eine Reihe von Faktoren besonders ausgeprägt. So gibt es beispielsweise kaum öffentlich zugängliche Informationen wie zum Beispiel Kundenbewertungen, die potenziellen Investoren ermöglichen würden, die Projekte oder Geschäftsideen vorab zu bewerten. Die Ersteller von Crowdfunding-Kampagnen sind daher in der Lage, die Qualität ihres Projektes oder ihrer Geschäftsidee übertrieben darzustellen oder wichtige Informationen zurückzuhalten, da sie den Informationsfluss zu den potenziellen Investoren steuern können. Viele der Projekte oder Geschäftsideen, die auf Crowdfunding-Plattformen präsentiert werden, sind zudem oft noch wenig ausgereift, wodurch sich die tatsächlichen Erfolgschancen nur schwer einschätzen lassen. Während in vielen anderen zweiseitigen Märkten Mechanismen wie Bewertungs- und Reputationssysteme eingesetzt werden, um die Informationsasymmetrien zwischen den Marktseiten zu verringern, lassen sich die meisten dieser Mechanismen aufgrund der spezifischen Besonderheiten von Crowdfunding-Plattformen hier nicht einsetzen. Für die potenziellen Investoren ist es daher extrem schwierig, die tatsächliche Qualität eines Projektes oder einer Geschäftsidee richtig einzuschätzen, bevor die Investitionsentscheidung getroffen werden muss. Die Dynamiken auf Crowdfunding-Plattformen unterscheiden sich daher von denen in anderen Plattform-Ökosystemen und es existieren noch viele offene Fragen in Bezug auf das optimale Marktdesign von Crowdfunding-Plattformen, um die Informationsasymmetrien zwischen den Marktteilnehmern zu reduzieren.

Vor diesem Hintergrund wurden vier Forschungsstudien durchgeführt, um zu untersuchen, wie die Verhaltensweisen und Entscheidungen der einzelnen Gruppen von Marktteilnehmern (d. h. Plattformbetreiber, Projektersteller und Investoren), die Entscheidungsfindung potenzieller Investoren auf Crowdfunding-Plattformen beeinflussen.

In der ersten Studie wird untersucht, welche Auswirkungen die Entscheidungen von Plattformbetreibern haben können. Genauer gesagt wird analysiert, wie sich die Dynamiken auf der Crowdfunding-Plattform Kickstarter dadurch verändert haben, dass der Plattformbetreiber eine Lockerung der bisher strengen Eingangskontrolle für neue Projekte durchgesetzt hat. Die zweite Studie befasst sich mit der Signalwirkung des Unterstützungsverhaltens und digitaler Mundpropaganda bisheriger Investoren für die Entscheidungsfindung zukünftiger Investoren. Auch die dritte Studie untersucht die Auswirkungen digitaler Mundpropaganda im Crowdfunding-Kontext, geht dabei jedoch konkret auf die Effekte gefälschter „Gefällt mir"-Angaben für bestimmte Crowdfunding-Projekte auf der Plattform Kickstarter ein. In der vierten Studie wird analysiert, wie die Projektersteller durch das Signalisieren bestimmter Persönlichkeitsmerkmale auf Basis der Projektbeschreibungen und des Kampagnenvideos das Investitionsverhalten der Unterstützer beeinflussen können.

Zusammengenommen zeigen die Ergebnisse der Studien, dass, als Folge der hohen Informationsasymmetrien zwischen Projekterstellern und Investoren auf Crowdfunding-Plattformen, potenzielle Investoren alternative Signale und Informationen suchen, die ihnen die Entscheidungsfindung erleichtern. Plattformbetreiber und Projektersteller können die Ergebnisse somit nutzen, um besser zu verstehen, wie sich das Verhalten der Gruppen von Marktteilnehmern auf potenzielle Investoren auswirkt. Die Erkenntnisse können daher verwendet werden, um das Marktdesign von Crowdfunding-Plattformen insoweit zu optimieren, dass Informationsasymmetrien abgebaut werden und ein Marktversagen dadurch auf lange Sicht vermieden wird.

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List of Abbreviations

AIC	Akaike information criterion
AON	All-or-nothing
API	Application programming interface(s)
CV	Control variable
DV	Dependent variable
DL	Description length
eWOM	Electronic word-of-mouth
FAQ	Frequently asked questions
FBS	Facebook shares
FFM	Five-factor model
GMM	Generalized method of moments
HCI	Human-computer interaction
HHI	Herfindahl–Hirschman index
IRF	Impulse response function(s)
IS	Information systems
JOBS	Jumpstart Our Business Startups
LIWC	Linguistic Inquiry and Word Count
NBRM	Negative binomial regression model
PC	Policy change
PVAR	Panel vector autoregression
RQ	Research question(s)
SD	Standard deviation
SE	Spelling errors
SP	Staff pick
TTW	Tweets on Twitter
UF	Update frequency
Web	World Wide Web
WOM	Word-of-mouth
ZIP	Zero-inflated poisson

1 Introduction

1.1 Motivation and Research Question

In recent years, platform-based business models have emerged as a prevalent organizational structure in many markets and industries. Platforms differ from traditional service providers in that they do not offer products or services by themselves and directly to their customers (platform end-users), but almost exclusively through so-called complementors who develop and deliver complementary content (e.g., apps, add-ons, plug-ins, modules, or extensions) via the platform. Prominent examples for such platforms include app stores such as the Apple App Store, which bring together app developers and smartphone users, and gaming platforms such as Steam, which bring together game developers and gamers. As these platforms are two- or multi-sided markets (cf., Economides and Katsamakas 2006; Eisenmann et al. 2006), they are characterized by distinct cross-side network effects, as each side derives externalities from the participation of the respective other group (Parker and Van Alstyne 2005; Rysman 2009; Ondrus et al. 2015). That is, only a platform that attracts sellers (complementors) will attract buyers (end-users) and vice versa. Creating favorable conditions for these network effects to emerge is thus at the core of platform management and platform providers face the enduring challenge to facilitate interactions and transactions between the market sides in order to create and maintain a thriving platform ecosystem (Rochet and Tirole 2003; Bakos and Katsamakas 2004).

Based on the concept of two-sided markets, crowdfunding platforms have become a prominent example of a successful platform-based business model and a wide variety of different crowdfunding platforms has emerged over the last few years. On these platforms, project creators can be considered the complementors who provide the complementary content for the platform in the form of crowdfunding campaigns, which, in turn, are financially supported by the end-users called backers. Crowdfunding enables project creators to collect relatively small financial contributions from a large number of backers through an open call on the internet (Schwienbacher and Larralde 2012). It thus creates a large, relatively undefined network of project stakeholders and consequently decreases the importance of more traditional investors such as angel investors or venture capitalists. As a result, the volume of the crowdfunding industry is predicted to surpass that of the venture capital industry in 2016 (Massolution 2015).

Compared to other types of two-sided markets, crowdfunding platforms are special because the transactions made via the platforms are particularly risky for end-users. The relationship between backers and project creators in crowdfunding can be considered from the perspective of principal-agent theory in order to examine this issue. The theory is concerned with the contractual relationship between a principal and an agent in which problems arise if the two contractual partners have different interests and information between them is asymmetrically allocated (i.e., the agent having more information), so that it becomes difficult for the principal to motivate the agent to act on his or her behalf (e.g., Jensen and Meckling 1976;

Eisenhardt 1989). In most crowdfunding models, the backer (acting as the *principal*) provides financial resources to the project creator (acting as the *agent*) with the expectation of receiving an adequate and attractive return on the investment (Norton 1995; Ley and Weaven 2011). However, the market design of crowdfunding platforms gives backers little control to ensure that the project creator uses the funds collectively invested by the backers for the purpose they were originally intended for, as a number of factors leave backers with a serious information disadvantage. First, given that there is little to no publicly available information such as customer reviews to evaluate the investment ex-ante, backers' primary source of information is the project description the creator has published on the crowdfunding platform. Even though this content allows prospective backers to develop an attitude towards the campaign and the respective project, this attitude is potentially biased due to the fact that it stems from a single source of information (Burtch et al. 2013). As project creators alone control the flow of information towards the backers, assessing the project creators' true motives as well as their determination and trustworthiness is particularly difficult for potential backers. While venture capitalists and angel investors disproportionately focus on local investments in order to avoid such issues by meeting entrepreneurs face-to-face as part of their due diligence process (Agrawal et al. 2016), this is rarely an option in online crowdfunding as it is neither possible nor feasible for potential backers. Project creators are therefore able to overstate quality or withhold information, putting backers at a disadvantage in the transaction (Mavlanova et al. 2012). The information asymmetry between backers and project creators will thus lead to issues of adverse selection, meaning that transactions are being made that would most likely not occur under perfect information (Akerlof 1970). Second, many of the projects published on crowdfunding platforms are still in their infancy, making it difficult for project creators, who are often unexperienced, to accurately predict project outcomes (Agrawal et al. 2014). Third, issues of moral hazard may arise (cf., Stiglitz 2000), meaning that project creators take greater risks because they might not necessarily have to fear legal consequences if they do not deliver a return on the backers' investments so that backers ultimately have to bear the costs if projects or ventures fail (Mollick 2014). Finally, while other platforms can address the issue of information asymmetry through a variety of established market mechanisms, the issue is more difficult to resolve in crowdfunding. For example, platforms such as eBay or Airbnb foster repeated transactions between complementors and end-users, making reputation a critical market mechanism on these platforms. However, as a crowdfunding campaign is most often a one-off process for the project creator, similar mechanisms can rarely be found on crowdfunding platforms.

As a consequence, the project creator often possesses information that the backer does not have and the backer is unaware of the characteristics (e.g., reliability) and behavioral intentions of the project creator. The actual utility of crowdfunding projects is therefore difficult to ascertain at the time the investment decision has to be made, as the motives and capabilities of project creators remain inscrutable to potential backers. Furthermore, 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 transactions in other types of two-sided markets, in which the product or service already exists (Agrawal et al. 2014;

Belleflamme et al. 2014). While a certain level of information asymmetry exists between the distinct market sides in every two-sided market, this issue is therefore amplified in the crowdfunding context and the dynamics of crowdfunding are thus different from those in other platforms settings.

As crowdfunding platforms only started to address a wider audience in the last few years, many open questions still remain with respect to the optimal market design of crowdfunding platforms in order to avoid information-related market failure in the long term. To influence the information asymmetry between project creators and backers, different mechanisms can be applied on the part of the platform provider, project creators as well as backers and these market design mechanisms are thus of great interest to researchers and practitioners alike. The thesis contributes to this area of research by examining how the behaviors and actions of the distinct groups of market participants (i.e., platform provider, project creators, backers), triggered by specific market design mechanisms, influence the decision-making of potential backers on crowdfunding platforms.

RQ: How do the behaviors and actions of the distinct groups of market participants in crowdfunding influence the decision-making of potential backers?

To contribute to answering this overall research question, four studies were conducted. The respective articles are included in this thesis and were previously published in information systems (IS) research outlets. The structure of this thesis is discussed in detail in the next section.

1.2 Thesis Structure and Synopses

This thesis is organized into seven chapters. Following the introductory chapter, the overall research context is presented in chapter 2, which concludes with a description of how the thesis is positioned in the research context. In order to answer the overall research question, four different studies were conducted and published in peer-reviewed outlets across four research articles. These articles constitute the chapters 3 to 6 and were slightly revised from the original published version in order to provide a consistent layout throughout the thesis. Figure 1-1 gives an overview of the dynamics that are examined in the individual articles and shows how they are positioned in the overall research context. Article 1 (chapter 3) deals with the effects of relaxing screening processes for projects on a crowdfunding platform on the behavior and decision-making processes of the market participants. In articles 2 and 3 (chapters 4 and 5), the effects of genuine and non-genuine social information in the form of social buzz and prior-contribution behavior on the decision-making of backers on crowdfunding platforms are investigated. The study described in article 4 (chapter 6) is focused on how the performance of crowdfunding campaigns is affected by the personality traits project creators signal via their project description and video. Chapter 7 concludes the thesis with a summary of the contributions to research and practice.

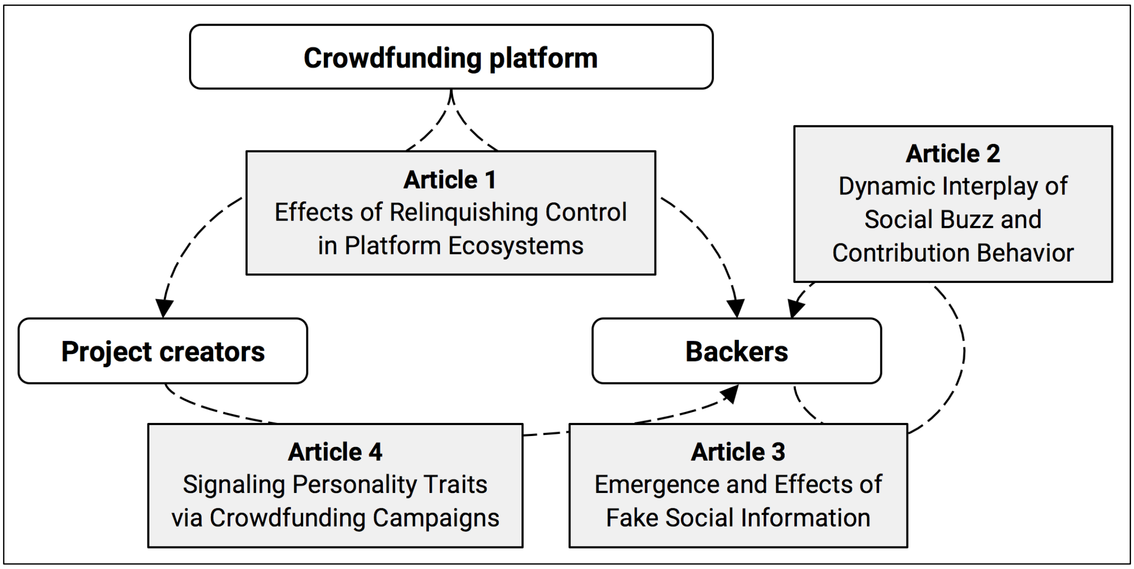

Figure 1-1 Overview of the Dynamics Examined in the Research Articles

In the following, short summaries of each of the four research articles (i.e., chapters 3 to 6) are provided, which include the motivation for the respective study, main findings, as well as the contribution to answering the main research question raised in the thesis. The summaries and the articles are written from the first-person-plural point of view (i.e., *we*) in order to express that these studies were conducted with co-authors and therefore also reflect their opinions.

Article 1

The Effects of Relinquishing Control in Platform Ecosystems: Implications from a Policy Change on Kickstarter

The platform provider of a crowdfunding platform naturally has the most power to influence the dynamics within the platform ecosystem. By making deliberate choices about decision rights, ownership, and control through platform governance mechanisms, the platform provider is able to influence the behavior of the market participants and their interactions, thereby contributing to the rise or fall of the platform. Drawing on IS control theory, we analyzed the effects that relaxing the previously stringent approval process for campaigns on Kickstarter, one of the dominant reward-based crowdfunding platforms, had for the decision-making processes of project creators and especially backers. Analyzing over 67,000 crowdfunding campaigns under conditions of a natural experiment, we show that the policy change in respect to the input control for campaigns led to a sharp increase in the number of campaigns available on the platform, while their average quality decreased. Before the policy change, being allowed to publish a campaign on Kickstarter could be considered a quality signal in itself, as passing the input control was a greater challenge for low-quality projects. The increasing number of campaigns on the platform therefore led to higher uncertainties for backers in respect to the quality of the individual projects, potentially further increasing the information asymmetries between the market sides. However, the results also suggest that by eliminating the inherent quality signal of the platform, the importance of the remaining signals increased and characteristics such as whether the campaign contained a video became more important for the potential backers' evaluation of campaigns. This study therefore contributes to answering the overall research question by showing that the policy design decisions on crowdfunding platforms can have a substantial impact on the dynamics among platform stakeholders, but also that decision cues are fragile and even subtle changes can have drastic consequences for the decision-making processes of backers.

Article 2

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

The study presented in the second article of the thesis is concerned with the effects the behaviors and actions of backers have on the decision-making of future backers. These effects are, however, not limited to internal platform dynamics. We therefore focused on the reciprocal relationship between social buzz on Twitter and Facebook, prior-contribution behavior on the crowdfunding platform Indiegogo, and the decision-making of backers on the same platform. By employing the panel vector autoregression (PVAR) methodology to analyze more than 6,300 crowdfunding campaigns, we show a positive influence of social buzz on project backing, implying that social buzz around a specific crowdfunding campaign is an important signal for potential backers to use for decision support. We also observe that backers try to minimize their risk of investing without receiving a reward and therefore invest in campaigns that are already successful in terms of the number of backers, suggesting strong positive feedback cycles on the crowdfunding platform. These results therefore highlight the importance of the behavior and actions of preceding backers for the decision-making of future backers, though biases such as herd behavior or informational cascades might also arise from following the actions of others.

Article 3

The Emergence and Effects of Fake Social Information: Evidence from Crowdfunding

The study presented in article 2 has revealed that social information such as social buzz has a significant effect on the decision-making in the crowdfunding context as it allows backers to better assess the quality of campaigns before investing. This effect might, however, also incentivize project creators to game the system by creating fake data in favor of their own campaign in order to deliberately mislead backers. The study described in article 3 contributes to signaling theory by showing why non-genuine social information might have an effect on consumer decision-making. This study is therefore concerned with the emergence and effects of fake social information in the form of non-genuine Facebook Likes in the crowdfunding context. Specifically, we captured unnatural, artificially created peaks in the number of Facebook Likes that a specific crowdfunding campaign received and observed subsequent campaign performance. Analyzing more than 35,000 campaigns on the platform Kickstarter, we found that 1.6% of all campaigns receive fake Facebook Likes. 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. Though the analysis therefore shows that non-genuine social information does, in fact, influence the investment decisions of backers, overall, manipulation activities have a negative effect on backing behavior. Thus, creating non-genuine social information can virtually backfire, as the campaign creators achieve the opposite of what they originally intended. This study therefore contributes to answering the overall research question by showing that signals, which are expected to reduce information asymmetries between project creators and backers, can be manipulated but the manipulation might not have the intended effects.

Article 4

Personality Matters: How Signaling Personality Traits Can Influence the Adoption and Diffusion of Crowdfunding Campaigns

Prior research has shown that investors such as venture capitalists and angel investors base a lot of their investment decision on the entrepreneurs themselves and consider specific personality traits prior to investing (MacMillan et al. 1985; Sudek 2006; Cardon et al. 2009; Chen et al. 2009). In order to determine whether backers on crowdfunding platforms go through similar decision-making processes prior to investing, the study presented in the final article of the thesis is concerned with the role of personality in the crowdfunding context. Drawing on the five-factor model of personality (FFM) and based on a sample of over 33,000 crowdfunding campaigns on Kickstarter, we analyzed whether the campaigns of project creators who are able to signal certain personality traits through their project description and video are more likely to succeed and to be shared via social media. The results show that project creators who are able to convey openness and agreeableness are more likely to succeed with their campaigns compared to those signaling neuroticism. The findings demonstrate that potential backers, as part of their vetting process, pay close attention to the way project creators present themselves and their projects on crowdfunding platforms.

In addition to the publications listed above, the following articles were also published or submitted for publication during my time as a Ph.D. candidate. These articles are, however, not part of the thesis:

Wessel, M., Thies, F., and Benlian, A. "The Implications of Increasing Platform Openness: Exploratory Evidence from a Policy Change on Kickstarter," (under review at the *Journal of Information Technology*).

Thies, F., Wessel, M., and Benlian, A. "The Implications of Relaxing Input Control for Entrepreneurial Crowdfunding Initiatives — Evidence from a Natural Experiment on Kickstarter," (under review at the *Information Systems Journal*).

Thies, F., Wessel, M., and Benlian, A. 2016. "Effects of Social Interaction Dynamics on Platforms," *Journal of Management Information Systems* (33:3), pp. 843–873.

Wessel, M., and Thies, F. 2015. "The Effects of Personalization on Purchase Intentions for Online News: An Experimental Study of Different Personalization Increments," *23nd European Conference on Information Systems*. Münster, Germany. (Best Paper Award - Full Research Paper).

Wessel, M., Thies, F., and Benlian, A. 2015. "A Lie Never Lives to Be Old: The Effects of Fake Social Information on Consumer Decision-Making in Crowdfunding," *23nd European Conference on Information Systems*. Münster, Germany.

Stadler, M., Thies, F., Wessel, M., and Benlian, A. 2015. " Erfolg von Crowdfunding-Kampagnen frühzeitig erkennen: Erfolgsprädiktoren auf Kickstarter und Indiegogo," *Wirtschaftsinformatik Proceedings*.

Thies, F., and Wessel, M. 2014. "The Circular Effects of Popularity Information and Electronic Word-of-Mouth on Consumer Decision-Making: Evidence from a Crowdfunding Platform," *22nd European Conference on Information Systems*. Tel Aviv, Israel.

2 Research Context

In this chapter, the research context of the thesis is presented in order to clarify the fundamental concepts. To do so, the first two sections 2.1 and 2.2 provide an introduction to the concepts of platforms and two-sided markets. Based on this theoretical foundation, the crowdfunding concept is introduced (section 2.3) and possible issues that might lead to market failure in this context are discussed (section 2.3.3). Based on these preceding sections, the positioning of the thesis in the research context is presented (section 2.4), concluding this chapter.

2.1 Platform Definitions and Distinctions

Platforms have become a ubiquitous phenomenon affecting almost all industries today, either within or across organizations. A platform has been generally defined as *"a set of stable components that supports variety and evolvability in a system by constraining the linkages among the other components"* (Baldwin and Woodard 2009, p. 19). Over the last two decades, two distinct but related types of platforms (product versus industry platforms) have emerged. The rise of these platform types has been accompanied by three separate but related waves of research in the field of product development (e.g., Wheelwright and Clark 1992; Meyer and Lehnerd 1997), technology strategy (e.g., Cusumano and Gawer 2002), and industrial economics (e.g., Rochet and Tirole 2003; Armstrong 2006). More recently, a separate stream of research has started to evolve in the IS field, as the notion of platforms is expanding beyond its traditional scope and becoming an all-pervasive trend in browsers, mobile app markets, web services, social media, online marketplaces, and gaming consoles (Tiwana et al. 2010; Tiwana 2014).

Initially, the term *platform* was used in the context of product development. Here, product (or internal) platforms are projects focused on increasing productive efficiency by producing variety at lower costs, thereby achieving economies of scale while allowing mass customization (Gawer 2009). Wheelwright and Clark (1992) introduced the term platform in this setting to refer to products that meet the needs of a core group of customers but are designed "*for easy modification into derivatives through the addition, substitution, or removal of features*" by deploying specific components in order to serve specific market niches (Wheelwright and Clark 1992, p. 5). Product platforms therefore provide a common structure upon which companies can efficiently develop and produce an entire product family and are thus especially common in sectors that involve manufacturing such as the automotive or consumer electronics industry (e.g., Gawer and Cusumano 2014).

In a second wave of research, industry (or external) platforms have been explored from the perspective of technology strategy, which are different from product platforms in that they provide a foundation in form of a product, service, or technology upon which outside firms are encouraged to build their own innovations. Product platforms and industry platforms therefore differ in respect to their scope, meaning that industry platforms are open to outside firms and managing a balance between retaining control and devolving autonomy to the outside firms has triggered a separate stream of research (e.g., Boudreau 2010; 2012; Benlian et al. 2015; Ondrus et al. 2015). Researchers also suggested different potential benefits of the two platform types. While the strategic intent behind implementing a product platform is to increase efficiency in product development processes through the reuse of common parts, allowing the production of a large number of derivative products, providers of industry platforms capture value from external, complementary innovations (Gawer 2009). An industry platform therefore becomes ever more valuable and increasingly difficult to dislodge by rivals or new market entrants as the number of its complementary innovations rises. This platform type therefore led to a shift towards a platform-centric competition among the platform providers, rather than between standalone systems or products. Many examples for industry platforms can be found in the computer industry and other information-technology industries where few dominant platforms compete intensively for the *platform leadership* within their market segment (Cusumano and Gawer 2002).

One of the most distinguishing features of industry platforms compared to product platforms is the potential emergence of network effects (or network externalities), meaning that with more users adopting the platform, the more valuable the platform becomes for its participants. This feature triggered a separate wave of research as industrial economists and IS scholars have adopted the platform concept and use the term to refer to products, services, or technologies that mediate transactions between and within the distinct groups of platform participants in two-sided (or multi-sided) markets (e.g., Rochet and Tirole 2003; 2004; Armstrong 2006; Eisenmann et al. 2006; Rochet and Tirole 2006; Tiwana et al. 2010; Tiwana 2014; Benlian et al. 2015). Though this research considers a more general scope (e.g., credit card payment networks or web services), it builds on the prior waves of research to explain the dynamics of platform competition. As this specific stream of research is extended by the research projects included in this thesis, it is considered in more detail in section 2.2.

Despite the different contexts platforms have evolved in, the fundamental architecture of all platforms is identical. Every platform architecture contains core components with low variety to allow high reusability and a set of peripheral components or modules with high variety but low reusability (Tushman and Murmann 1998; Baldwin and Woodard 2009; Tiwana et al. 2010). While the stable low-variety components constitute the platform itself, the high-variety components complement the platform's core functionalities by interoperating with the core components through pre-specified interfaces. These peripheral components have therefore often been described as *complements* in the extant literature, while the developers of these complements have been referred to as *complementors* (Gawer and Cusumano 2014). Collectively, a platform and its complements (and complementors), functioning as a unit, form a platform ecosystem (Cusumano and Gawer 2002).

2.2 Two-Sided Markets and Network Effects

Many of the most successful products, services, or technologies that have refined entire industries over the last few decades are platforms that bring together two or more distinct groups of market participants in a network and mediate interactions between them[1]. These two-sided (or multi-sided) markets are characterized by network effects that exist between the distinct groups of market participants. While network effects are a common phenomenon for many technologies such as the telephone, where every adopter benefits from a growing overall user or installed base (Katz and Shapiro 1985), two-sided markets are special because these externalities may exist both within as well as across the distinct market sides (Figure 2-1). Cross-side (or indirect) network effects therefore exist if either side of the market derives benefits from the participation of members on the respective other side (Bakos and Katsamakas 2004). Same-side (or direct) network effects, however, exist if these benefits arise from the participation of members on the same side of the market. These externalities can be both positive as well as negative. For example, developers in a mobile app market benefit from a rising number of mobile phone users on the other side of the market, potentially leading to a higher number of downloads or sales. The mobile phone users also profit from an increasing number of developers, as they can expect higher numbers of apps and thus more choice. Though the cross-side network effects in this example are therefore positive, the same-side network effects on the developer side of the market will likely be negative, as too many developers may discourage others from making the investment to join.

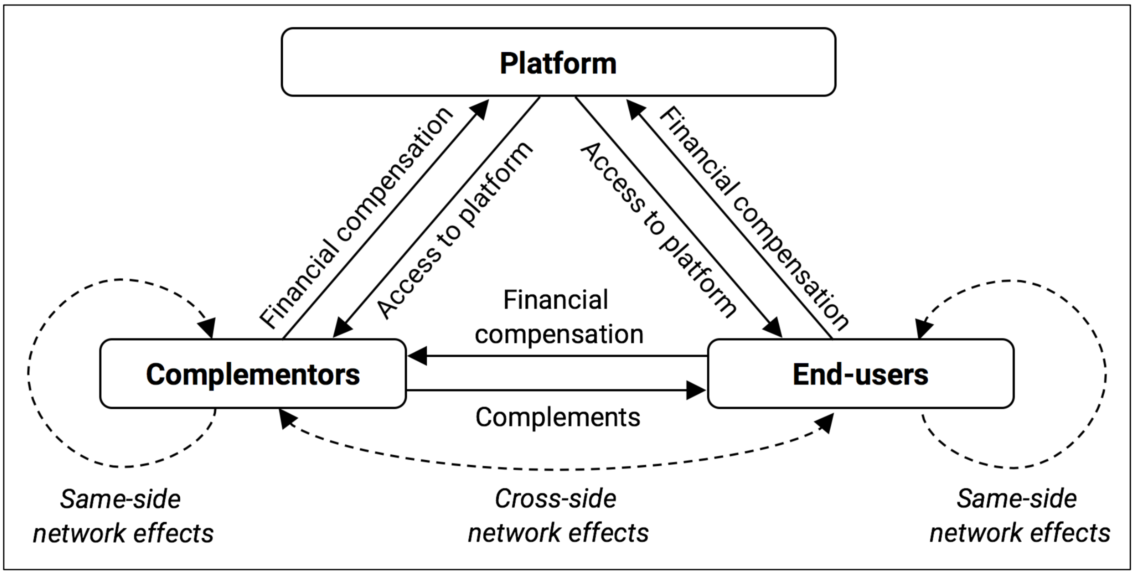

Figure 2-1 Value Creation and Network Effects in Two-Sided Markets

The literature on two-sided markets has, so far, been mainly focused on these network externalities (e.g., Bakos and Katsamakas 2004; Eisenmann et al. 2006; Tucker and Zhang 2010) and the coordination problems that arise from them, primarily in respect to pricing (e.g., Rochet and Tirole 2003; Parker and Van Alstyne 2005; Armstrong 2006; Rysman 2009).

[1] There is no consensus among researchers on whether all two-sided markets can also be considered platforms. While Eisenmann et al. (2006, p. 2) define all *"products and services that bring together groups of users in two-sided networks"* as platforms, Gawer and Cusumano (2014, p. 422) highlight that not all two-sided markets are platforms in the traditional sense. The argument is that two-sided markets that purely facilitate an exchange or trade (e.g., dating bars) do not stimulate an external innovation based on an underlying platform.

Due to the interdependencies between the market sides, a *chicken-and-egg* problem may arise, as end-users only come aboard if complementors provide a sufficient number of complements and vice versa (Parker and Van Alstyne 2005). A common strategy to overcome this problem is to follow a *divide-and-conquer* pricing strategy by subsidizing one side of the market (divide), while recovering losses from the respective other (conquer), in order to grow both (Caillaud and Jullien 2003). Platform providers can therefore internalize the externalities between the market sides by setting prices more efficiently (Parker and Van Alstyne 2005). Determining which side to subsidize based on cross-price elasticities is therefore an essential element of platform management.

Opportunities to create two-sided markets may arise in situations in which *"there are externalities and in which transaction costs, broadly considered, prevent the two sides from solving this externality directly"* (Schmalensee and Evans 2007, p. 154). Platforms such as Uber and Lyft could therefore emerge because they provide a technology to match an independent driver owning an under-used asset in form of a vehicle with a passenger willing to pay to employ the asset. Prior to the existence of these platforms, the transaction costs involved in matching passengers with drivers (e.g., for searching, contacting, contracting, paying) inhibited the development of such a peer-to-peer transportation market.

Though two-sided markets are common in *old-economy* industries (e.g., advertising-supported media), the internet and especially the world wide web (web) have accelerated this trend and there are many examples of companies that, by relying on this organizational structure, have seen unprecedented growth rates. By focusing on enabling interactions and eventually transactions between the distinct sides of the market, two-sided markets are fundamentally different from traditional product or service offerings. In the traditional value chain, the value is created from left to right (figuratively speaking), where costs are on the left and revenue is on the right (Eisenmann et al. 2006). In contrast, while managing the market sides in two-sided markets may create costs on either side, both sides can also generate revenue for the platform provider (Figure 2-1), though as discussed above, one side is often subsidized (Hagiu 2014). Many industries that have previously been characterized by a vertical integration, meaning that companies control the entire value chain either through contract or direct ownership, have been disrupted by or are increasingly moving towards a two-sided market business model (Hagiu and Wright 2015). For example, Uber and Airbnb have disrupted the traditional taxi service and hotel industries without owning any vehicles or real estate, respectively.

2.3 Crowdfunding

Crowdfunding allows project creators or entrepreneurs to collect financial contributions from supporters through an open call, mostly on the internet, without standard financial intermediaries (Schwienbacher and Larralde 2012; Mollick 2014; Cholakova and Clarysse 2015). The concept is built on the broader concept of crowdsourcing, which involves engaging the *crowd* to generate ideas or solutions for corporate activities (e.g., Poetz and Schreier 2012; Bayus 2013; Huang et al. 2014). Crowdfunding, however, is focused on reaching a monetary (project) goal by convincing the crowd to individually contribute small financial investments instead of choosing the traditional fundraising approach of receiving large contributions from a small number of investors. Crowdfunding platforms can therefore be considered two-sided markets, as they facilitate these transactions and network externalities exist between the two market sides (see section 2.3.2). In this setting, the crowdfunding platform itself is used to exchange information on the projects ought to be financed through the so-called crowdfunding campaigns, while also providing the necessary infrastructure for payments and the communication between the market sides. In crowdfunding platform ecosystems, the campaigns can therefore be considered the compliments, provided by project creators or entrepreneurs (complementors) and supported by backers (end-users).

Over the last few years, several different crowdfunding platforms have emerged and four distinct models of crowdfunding have been distinguished: equity-based, lending-based, reward-based, and donation-based (Kuppuswamy and Bayus 2014). These four models mainly differ with respect to the return backers can expect from their contribution, which can either be financial, materialistic, idealistic, or philanthropic in nature (Ahlers et al. 2015). Equity- and lending-based crowdfunding markets, for instance, offer financial returns for backers, either indirectly through company equity or directly through interest. In reward-based crowdfunding, backers can expect non-financial tangible benefits for their investment. Finally, in donation-based crowdfunding markets, backers cannot expect any financial or tangible returns and thus pledge due to altruism and warm glow (Andreoni 2006).

All four crowdfunding models have generally shown strong growth over the last few years, leading to a considerable volume of the crowdfunding market, which is predicted to surpass that of the venture capital industry in 2016 (Massolution 2015). The research projects included in this thesis have, however, been invariably focused on reward-based crowdfunding as a research setting, because in order to answer the overall research questions, this model can be considered the most suitable one from a research perspective. First, equity-based crowdfunding has, in the past, been surrounded by several legal controversies that restricted the global proliferation of this model. While these issues have been partially resolved by national initiatives such as the Jumpstart Our Business Startups (JOBS) Act in the United States, platforms focused on equity-based crowdfunding such as SeedInvest generally still offer very few investment opportunities simultaneously. The reason is that these platforms apply rigorous screening and due diligence processes before allowing projects to seek funding via their platform for legal reasons (SeedInvest Technology 2015b). Equity-based crowdfunding platforms are therefore considerably less dynamic (i.e., focused on long-term investments of at least 5-7 years) and more complex compared to the other models. Decision-making processes on these platforms therefore tend to be slower due to the heightened regulations and higher average investment amounts (SeedInvest Technology 2015a). Second, while the lending-based crowdfunding model has received considerable attention among researchers so far (e.g., Galak et al. 2011; Herzenstein et al. 2011b; Allison et al. 2013; Allison et al. 2015; Moss et al. 2015), on platforms such as Kiva.org backers are often not focused on receiving a return on their investment and rather invest due to prosocial motives (Allison et al. 2015). Other lending-based crowdfunding platforms such as Prosper.com are not project-oriented and rather coordinate the financing of personal loans for individuals. Finally, as no tangible returns can be expected in donation-based crowdfunding, effects of asymmetric information on the decision-making of backers will be less severe in this setting and prior research has often rather focused on possible bystander or crowding-out effects that may arise in this setting (Burtch et al. 2013).

2.3.1 Specific Characteristics of Reward-Based Crowdfunding

The campaign is the primary source of information for backers in all crowdfunding models, allowing them to vet the investment before committing. Most reward-based crowdfunding platforms use the same content elements and a common structure made up of two separate sections to present campaigns as illustrated in Figure 2-2. The top section is designed so that potential backers can easily and quickly retrieve the most fundamental information about the campaign and the respective project. This section consists of the campaign title, possibly a tagline or short description, a video or pictures highlighting the most important project characteristics, campaign statistics (i.e., funding goal, amount already invested, number of backers, remaining time, etc.), geographical location, relevant tags or categories, buttons to share the campaign on social media, and a short profile of the project creator(s). Should potential backers deem the campaign interesting after considering the basic information in the top section, they can scroll down in order to retrieve more extensive information from the bottom section. This section contains a detailed description of the project that often includes additional pictures to show product prototypes and a timeline of critical project milestones as well as a list of risks and challenges that need to be addressed in order to achieve a successful project outcome. Backers are also able to access project updates and comments via this section. Updates are written by project creators to clarify certain aspects of the project and respond to frequent inquiries from backers, while comments can be used by backers to discuss certain aspects of the project with fellow backers or the project creator. Finally, the bottom section also contains a list of the rewards backers can expect as a return on their investment, depending on the investment amount (see Figure 2-2).

Prior research on reward-based crowdfunding has found that the rewards backers receive as a return on their investment are a central reason for them to invest (value for money), while other, more intrinsic motives such as helping others, being part of the community, and supporting the cause also exist (Gerber and Hui 2013; Kuppuswamy and Bayus 2014; Cholakova and Clarysse 2015). 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 that is being developed for an investment of hundreds of dollars, therefore essentially allowing the project creators to sell products that do not yet exist (Belleflamme et al. 2014). By offering the rewards and selling them to backers, the project creators attempt to reach the campaign's funding threshold set at the beginning of the campaign runtime. As most reward-based crowdfunding platforms follow the *all-or-nothing* (AON) funding model, project creators will only be able to receive any of the capital raised if the threshold is reached. Project creators therefore have a motive to overstate quality or withhold information in order to persuade as many backers as possible to invest. Backers thus face high uncertainties as to the actual quality of the project and the comprised rewards, which remains highly unpredictable at the time of the investment. If no other trustworthy information is available, market failure situations such as adverse selection and moral hazard may arise, caused by the asymmetric information between project creators and backers. This issue is discussed in more detail in section 2.3.3.

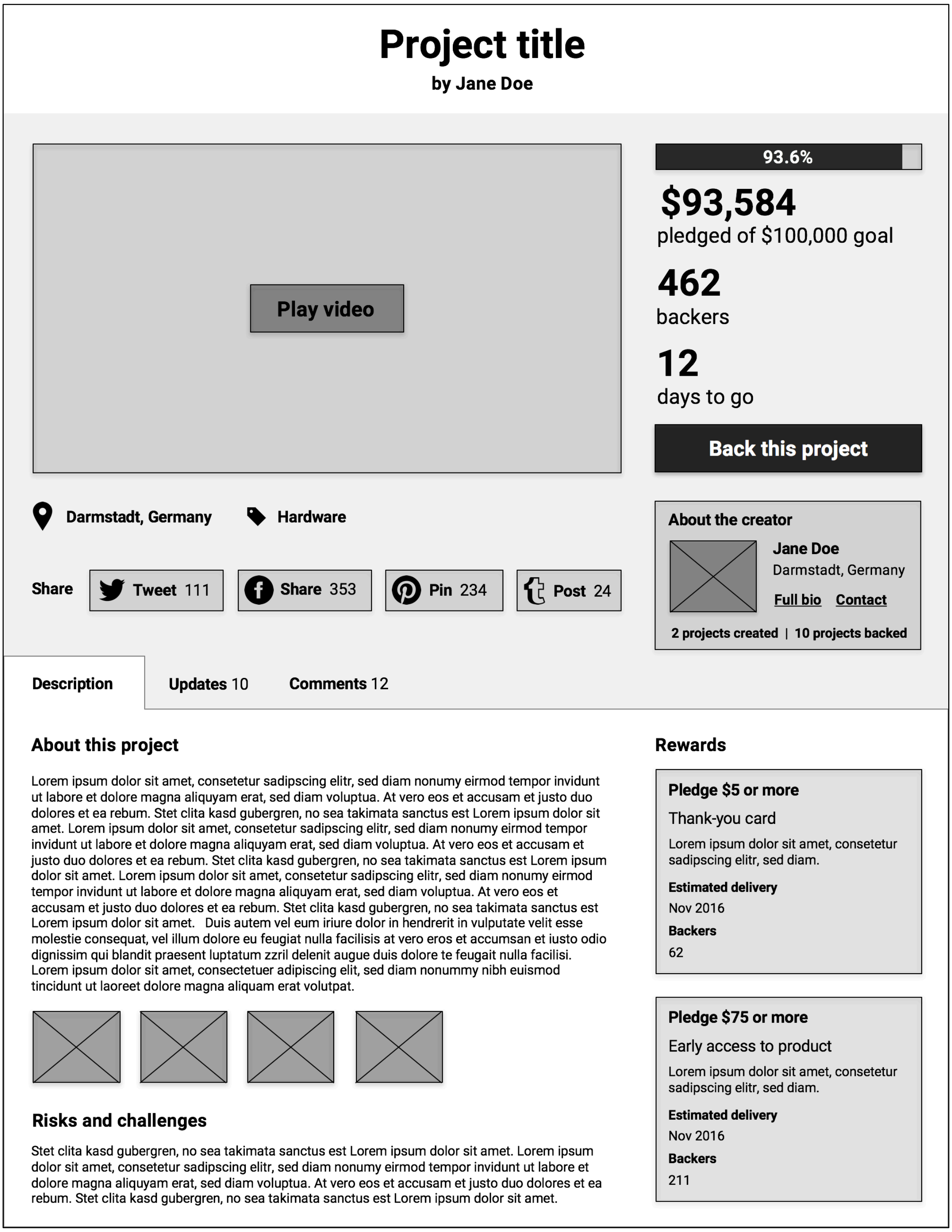

Figure 2-2 Common Structure and Content Elements of Campaigns on Reward-Based Crowdfunding Platforms

2.3.2 Network Effects on Crowdfunding Platforms

On crowdfunding platforms, project creators and backers constitute the two sides of the market, while their relationship is facilitated and managed via the platform itself. One-to-many relationships are established between individual project creators and a certain number of backers, once the backers support the project creator's campaign on the platform financially. Backers, in turn, expect some kind of return on their investment, provided that the financial support is not considered a donation. Each side of the market therefore depends on the participation of the respective other side so that they exert cross-side network effects on each other (see Figure 2-3).

The external effects of backers on project creators are unambiguously positive, as a larger crowd of backers increases the chances for project creators to reach their desired funding goal. Given that most crowdfunding platforms attract very different types of projects that are assigned to specific categories such as art, design, games, or technology, it can be assumed the preferences of potential backers visiting the platforms are also rather heterogeneous (Rochet and Tirole 2003; Armstrong 2006). Crowdfunding platforms therefore need to facilitate coordination by guiding backers to the most appropriate campaigns in order to make use of the externalities backers exert on project creators and in order to avoid coordination or market failures (Belleflamme et al. 2015). As agent heterogeneity is often limited in other platform settings (e.g., Uber or Airbnb), facilitating coordination between the market sides is far less complex, making the matching problem trivial in these markets (Fung and Hsu 2015).

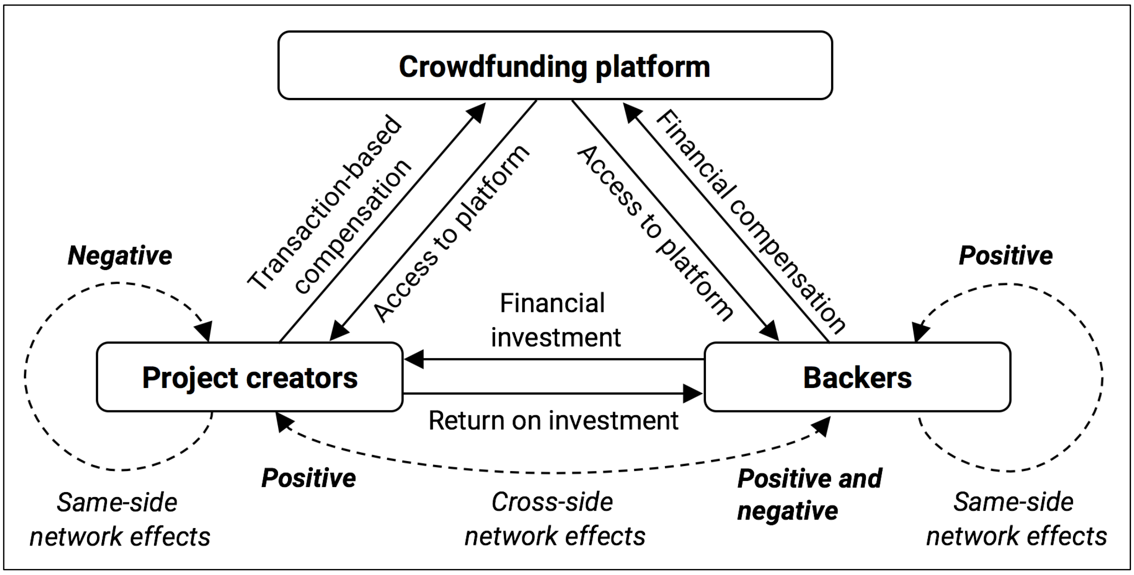

Figure 2-3 Value Creation and Network Effects on Crowdfunding Platforms

The external effects in the opposite direction, from project creators to backers, are rather ambiguous. First, as more project creators correspond with more campaigns being available on the platform, it becomes increasingly more likely that potential backers encounter campaigns that correspond with their personal preferences and tastes. However, if the crowdfunding platform fails to guide potential backers to campaigns according to their preferences, more campaigns being available on the platform might lead to higher search costs for backers or failing campaigns due to a suboptimal allocation of backers to campaigns (see Belleflamme et al. (2015, p. 16) for a stylized example). Furthermore, everything else being equal, more campaigns reduce the average funding amount each project creator can expect from the crowd, decreasing the likelihood that any given campaign will achieve its funding threshold. As depicted in Figure 2-3, the cross-side network effects of project creators on backers can therefore be positive as well as negative, while the positive effects are likely to prevail.

Same-side network effects can also be expected to be present on crowdfunding platforms within the respective market sides. With a rising number of project creators on the platform and therefore an intensifying competition, it will become increasingly difficult for an individual project creator to gather a sufficient number of backers to surpass the funding threshold, suggesting that the same-side network effects among project creators are negative. In contrast, effects among backers will primarily be positive. As the goal of backers is to support campaigns that eventually are successful in reaching the funding threshold so that a return on the investment can be expected, backers benefit from the participation of other backers as they increase the campaign's likelihood of success. Backers can also derive externalities from the participation of other backers through their funding decisions. As the information asymmetry between project creators and backers might be high, more backers investing in a specific campaign could be seen as a quality indicator. However, biases such as bandwagon effects that might arise in these situations could have negative consequences for subsequent backers. These issues are discussed in more detail in section 2.3.3.

2.3.3 Dynamics and Asymmetric Information Problems on Crowdfunding Platforms

Similar to other two-sided markets, decision-making processes on crowdfunding platforms are characterized by asymmetric information between the two market sides. In crowdfunding, project creators will, in most cases, have considerably more information about their project and its quality than backers. Backers are only aware that some projects on the platform are of good quality, while the rest is of bad quality (Akerlof 1970). Compared to other platforms that are two-sided markets, the problem of asymmetric information is, however, more severe in the crowdfunding context and two main issues might arise. First, all investment decisions on crowdfunding platforms are being made before the actual quality of the project can be effectively evaluated after the campaign has ended (similar to experience goods). Transactions on other platforms such as eBay and Airbnb are often sequential and many transactions can be made and rated over a short period of time, allowing individuals on the buying side of the market to learn from the experiences of their predecessors. eBay or Airbnb are also designed so that market participants are incentivized to build up a reputation and trust with each other by rating the performance of the respective other party after each transaction. Though biases might arise in such reputation systems (e.g., Ye et al. 2014; Zervas et al. 2015), they have become a widespread and successful measure to prevent fraud and similar issues in platform settings. As a crowdfunding campaign is most often a one-off process for the project creator, similar reputation mechanisms can rarely be found on crowdfunding platforms. It is therefore particularly difficult for backers to distinguish between low-quality and high-quality projects, as they are unable to assess the true quality and could thus make suboptimal choices due to the potentially biased information provided by project creators.

Second, though outright fraud occurs on crowdfunding platforms as project creators make use of the high level of information asymmetry by overstating quality or withholding information, thus passing off a low-quality project as a higher-quality one, project creator incompetence and general project risks can be considered to be more serious issues (Tomboc 2013; Agrawal et al. 2014). With the exception of equity-based crowdfunding, raising funds through crowdfunding platforms is still subject to little regulation. While the more traditional sources of funding such as venture capitalists and angel investors would address quality, legal, and ethical issues during a vetting process, especially reward-based crowdfunding platforms often allow project creators to bypass intensive screening processes, leading to relatively high failure rates. On the popular reward-based crowdfunding platform Kickstarter, 9% of project creators fail to deliver the promised rewards to backers, while those who deliver are often unable to adhere to the estimated delivery date (Mollick 2015). These problems arise as project creators are often inexperienced and projects are posted on the platforms in an early stage of their development, when there are still significant uncertainties concerning their outcomes, making the project plan that is posted on the platform a *"little more than an educated guess"* (Tomboc 2013, p. 267).

Though backers have, in the past, been rather optimistic about project outcomes and the project creators' ability to deliver the promised rewards (Agrawal et al. 2014; Mollick 2015), the mentioned issues make it increasingly difficult for backers to distinguish between good and bad investments. Consequently, backers could become reluctant to invest higher amounts in order to reduce their risk in the face of uncertainty, making the crowdfunding platform less attractive for project creators with innovative and complex projects that require more funding. The information asymmetry between project creators and backers could therefore potentially lead to market failure situations such as adverse selection (ex-ante) and moral hazard (ex-post), meaning that value-creating transactions between the markets sides (see Figure 2-3) will no longer be executed (Agrawal et al. 2014). As the information problem therefore threatens the crowdfunding business model, signals, factors, strategies, and biases that affect the level of information asymmetry between project creators and backers on crowdfunding platforms are of considerable interest for scholars and practitioners alike. Table 2-1 lists mechanisms that can be applied on the part of any of the three groups of market participants and that could be possible determinants of the level of information asymmetry on crowdfunding platforms. While some of the mechanisms have already been examined in prior research (see Table 2-1), many remain uninvestigated in the crowdfunding context so far, despite their relevance in other platform settings. The studies described in the articles that are included in the thesis therefore examine mechanisms that have been left unexplored, or underexplored, in prior research.

Table 2-1 Possible Determinants of Information Asymmetry on Crowdfunding Platforms

Market participants	Mechanism	Literature examples
Platform providers	Applying industry regulations	–
	Certification	–
	Insurances	–
	Platform rules and policy design	–
	Press and social media	–
	Recommender systems	–
	Reputation systems	–
	Screening and input control	Weiss et al. (2010)
Project creators	Portfolio effects	Freedman and Jin (2011)
	Social capital, social networks, and social media	Lin et al. (2013)
	Trust	Duarte et al. (2012)
	Other information or signals (e.g., funding goal, funding period, geographical location, personality traits, rhetorical techniques, video, fake signals)	Herzenstein et al. (2011b); (Mollick 2014); Allison et al. (2015); Moss et al. (2015)
Backers	Herd behavior and informational cascades based on prior contributions	Herzenstein et al. (2011a); Zhang and Liu (2012)
	Social media	–
	Syndicates	Agrawal et al. (2016)

Note: *The literature mentioned covers all four models of crowdfunding. Parts of the list have been adopted from Agrawal et al. (2014); Beaulieu et al. (2015); Belleflamme et al. (2015).*

When looking at Table 2-1, it becomes evident that the role of platform providers in influencing information asymmetries has been largely overlooked so far. However, the provider of a crowdfunding platform naturally has the most power to influence the dynamics within the platform ecosystem. Platform providers, acting as intermediaries between project creators and backers, play an important role, as they create and enforce platform governance mechanisms by making deliberate choices about decision rights, ownership, and control with respect to the platform in order to appropriately engage the other platform stakeholders (Ghazawneh and Henfridsson 2013; Benlian et al. 2015). For instance, platform providers can enact screening or input control mechanisms for projects submitted to a crowdfunding platform based on specific rules in order to ensure a certain level of quality on the platform, thereby reducing investment risks for backers.

Project creators and backers can also try to solve the problems of asymmetric information directly through signaling (e.g., Spence 1973; 2002) or screening (e.g., Stiglitz 1975) without relying on the platform provider as an intermediary to regulate the transactions. Signals are actions taken by the informed agent (i.e., project creator) in an attempt to reveal private information to the principal (i.e., backer). In crowdfunding, project creators can, for example, try to mitigate uncertainties by signaling competence through experience or education. With screening, on the other hand, the principal attempts to learn as much as possible about the agent and tries to incentivize the agent to disclose private information. However, as an individual backer can exert little control over project creators, screening will rarely be expedient in the crowdfunding context. Prospective backers can, instead, observe the actions taken by their predecessors in an attempt to reduce their own investment risk in the face of uncertainty about the proposed new project. Rational herd behavior or informational cascades may therefore evolve on crowdfunding platforms, meaning that backers will tend to contribute to campaigns that have already received a lot of support from the community either in terms of funding or in terms of social buzz, as this support implies superiority over other, less successful projects. This means that backers can, intentionally or unintentionally, steer the decision-making processes of future backers through their own contribution behavior.

2.4 Positioning of the Thesis

Though crowdfunding, in the modern sense of the term, dates back to the early 2000's when the first platform ArtistShare for creative artists was started, the concept only gained mainstream success around 2010 after platforms with a wider appeal such as Kickstarter and Indiegogo were launched. Most crowdfunding platforms are therefore still relatively new means to raise capital and the whole industry is still in its infancy. Many open questions remain with respect to the optimal market design in order to avoid market failure in the long run. As the information asymmetry between project creators and backers can be considered one of the main issues in this respect (see section 2.3.3), market design mechanisms that help to prevent information-related market failures are of great interest to researchers and practitioners alike (Agrawal et al. 2014). Despite the importance of reducing information asymmetry in the crowdfunding context and though a number of previous studies exist, the research is still far from conclusive. Belleflamme et al. (2014) explicitly call for further research in order to resolve asymmetric information issues on crowdfunding platforms, while linking the crowdfunding topic with the ongoing research on platforms and two-sided markets. This topic provides the common problem domain for the articles included in the thesis and the thesis contributes to this research area by examining how the behaviors and actions of the three distinct groups of market participants (i.e., platform provider, project creators, and backers) influence the decision-making processes of future backers.

3 Effects of Relinquishing Control in Platform Ecosystems

Title

The Effects of Relinquishing Control in Platform Ecosystems: Implications from a Policy Change on Kickstarter[2]

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Abstract

Managing platform ecosystems requires the providers to maintain a delicate balance between retaining control and devolving autonomy to complementors in order to encourage contribution and innovation. In this study, we make use of a policy change that abolished the previously mandatory approval process for campaigns on Kickstarter, one of the dominant reward-based crowdfunding platforms. Analyzing a total of 67,384 Kickstarter campaigns under conditions of a natural experiment, we find that abolishing the input control was a double-edged sword for Kickstarter's ecosystem: While the average platform revenue increased after the policy change, it became more volatile, and while project diversity increased, average campaign quality decreased. Project creators are now confronted with an even higher level of competition, while backers face greater uncertainties about campaign quality, which shifts their focus to alternative quality signals. The new strategy might threaten Kickstarter's unique status as a high-quality platform in the striving business of crowdfunding.

Keywords

Crowdfunding, platform ecosystems, platform openness, policy change, input control, two-sided markets, natural experiment

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3.1 Introduction

In the last few years, the concept of crowdfunding has attracted considerable attention among practitioners and scholars alike. It enables the creators of entrepreneurial, social, or creative projects to fund their efforts by collecting rather small contributions from a large number of individuals through an open call on the internet (Schwienbacher and Larralde 2012; Mollick 2014). The success of the crowdfunding concept can largely be attributed to the numerous crowdfunding platforms such as Kickstarter and Indiegogo that provide the necessary infrastructure to facilitate transactions between the distinct user groups. Like other two-sided markets (also referred to as multi-sided platforms), these platforms primarily create value by enabling interactions between groups of customers or other stakeholders, creating cross-side network effects among them (Eisenmann et al. 2006). In the context of crowdfunding, the platform provider, together with project creators (also referred to as complementors), and project backers (end-users) form a platform ecosystem (Cusumano and Gawer 2002).

Though economics and strategies for two-sided markets have been the subject of a variety of publications in research areas such as marketing, economics, and information systems in the past (e.g., Rochet and Tirole 2003; Armstrong 2006; Rysman 2009), little is known about what constitutes healthy and viable platform ecosystems in the context of crowdfunding. Specifically, governing crowdfunding platforms requires the owners of the platform to manage a delicate balance between retaining control and devolving autonomy to the project creators in order to encourage them to contribute appealing crowdfunding campaigns (Boudreau 2010; Tiwana et al. 2010; Boudreau 2012). In fact, one of the key differential factors between the major crowdfunding platforms that exist today is their approach towards input control. Input control is a form of formal control or gatekeeping that *"represents the degree to which the platform owner uses predefined objective acceptance criteria for judging"* which campaigns and project creators are allowed into their platform ecosystem (Tiwana 2014, p. 123). For instance, Indiegogo and Kickstarter, the largest reward-based crowdfunding platforms today, have taken different approaches to openness in terms of the input control they apply. While Indiegogo is completely open in that the platform does not apply any input control mechanisms for project creators and thus allows any individual or organization to start a campaign on their platform, Kickstarter has, from its beginning, chosen to apply input control with a rigorous green-lighting process, meaning that every campaign has to be approved by Kickstarter staff manually before it can be published on the platform. These approaches to input control applied by Kickstarter and Indiegogo can be compared to those taken by Apple and Google in the mobile app market. While Google's Play Store, similar to Indiegogo, does not apply input control mechanisms apart from security checks, Apple's App Store is well known for enacting strict policies to control the quality of apps published on the platform. Though applying such mechanisms is costly and can lead to lower numbers of apps or campaigns available on the platform, in turn, they have made being published on platforms such as Apple's App Store and Kickstarter a quality signal in itself (Mitroff 2012).

In June 2014, however, Kickstarter implemented a policy change and now allows project creators, similar to Indiegogo, to start campaigns on their own terms without requiring any approval from Kickstarter staff. Kickstarter motivated the change with the expectation that it would make the platform easier to use and open it up to new kinds of projects (Strickler 2014). While Kickstarter did not reveal the strategic intentions behind the decision to abandon the screening process, the platform has, in the past, lost lucrative projects to competing platforms such as Indiegogo due to the previously strict policies (Jeffries 2014; Kelion 2014). However, not imposing any input control to ensure quality might lead to a fragmented platform flooded with low-quality content (Coughlan 2004; Bresnahan and Greenstein 2014).

The policy change gives us the unique opportunity to study the health of Kickstarter's ecosystem before and after this shock, which is considered to be endogenous to the platform provider Kickstarter but exogenous for the other platform participants, namely, project creators and backers. We want to understand the effects Kickstarter's decision to remove the high entry barriers—and thus to open their formerly rather closed platform—had on the platform ecosystem by analyzing how backers and project creators reacted to the change and how potential drivers of campaign success changed in response. The policy change thus allows insights into the effects that input control mechanisms have on the success of crowdfunding platforms. Our research is guided by the following research questions:

RQ1: How does relinquishing input control affect the platform participants and their behavior?

RQ2: How are the drivers of campaign success affected by the change in input control?

Analyzing a total of 67,384 Kickstarter campaigns that cover the period from December 2013 to December 2014, we found that abolishing input control was a double-edged sword for Kickstarter's ecosystem: While we see a strong increase in the average number of new campaigns per day and a significant rise in Kickstarter's revenue, the policy change led to lower average campaign quality and success rates, making the platform less attractive for project creators and backers alike.

Our study contributes to the IS control and still nascent platform ecosystem literature in three important ways. First, ours is one of the first studies to conceptualize and examine input control as a formal control mechanism and to show how its abolishment affects platform participants and their behavior. Prior IS research has focused on output, process, and clan control, but inadvertently neglected input control (e.g., Kirsch et al. 2002; Choudhury and Sabherwal 2003). Our study therefore complements previous IS control studies and demonstrates that input control gains a newfound relevance in platform markets. Second, we add to the growing stream of research on the implications of policy changes on the dynamics within platform ecosystems (e.g., Claussen et al. 2013; Burtch et al. 2015). In this regard, our study is the first to examine the effects of a policy change in respect to control mechanisms under conditions of a natural experiment. Finally, and more broadly, our study also shows that policy changes can significantly shift the relative importance of signals for the decision-making of platform users. Therefore, for the providers of platform ecosystems, it is important to realize that decision-making processes of users can not only be affected by adjusting governance strategies but also that decision cues are fragile and even subtle changes can have drastic consequences for the dynamics among platform stakeholders.

The remainder of the paper is structured as follows: First, the theoretical background is laid out, followed by a description of the research context. Next, we describe our data and research methodology and our descriptive as well as econometric evidence. In the concluding section, we discuss the implications for research and practice and point out the paper's limitations, as well as promising areas for future research.

3.2 Theoretical Background

3.2.1 Governance and Control in Platform Ecosystems

Similar to other platform providers, the owners of crowdfunding platforms face the challenge of aligning their own objectives with those of the other stakeholders within the platform ecosystem, namely, the project creators and backers. Cross-side network effects among the distinct groups of stakeholders typically characterize these platform ecosystems, as each side derives positive externalities from the participation of the respective other groups (Bakos and Katsamakas 2004; Benlian et al. 2015). For instance, the success of a crowdfunding platform strongly correlates with the availability of compelling campaigns that attract a sufficient number of interested backers. However, project creators will only be willing to contribute campaigns if the platform provides sufficient incentives to do so, such as a reasonable commission on profit (Rochet and Tirole 2003). The platform providers therefore need to create and enforce governance mechanisms by making deliberate choices about decision rights, ownership, and control with respect to the platform and by establishing regulating guidelines and rules in order to appropriately engage other platform stakeholders (Ghazawneh and Henfridsson 2013; Benlian et al. 2015). Platform governance is generally defined as *"who makes what decisions about a platform"*, where the main challenge for platform providers is to *"retain sufficient control to ensure the integrity of the platform while relinquishing enough control to encourage innovation"* (Tiwana et al. 2010, p. 679).

Though platform governance can be studied from three distinct perspectives (Tiwana et al. 2010), namely, decision rights, ownership, and control, we focus on the latter perspective in this study, as the decision rights and ownership mainly reside with the platform owner in the context of crowdfunding and remain unaffected by the policy change. Control refers to mechanisms used by controllers in the attempt to influence controlees so that they act and behave in accordance with the controller's objectives and goals (Ouchi 1979; Kirsch 1997). In the context of crowdfunding, the platform owner serves as the controller, while the project creators can be referred to as the controlees.

In previous research, two main categories of control have been distinguished, namely, formal and informal control (e.g., Kirsch 1996). Within formal control, two distinct modes, output (also referred to as outcome) and process (also referred to as behavior) control, have been observed (e.g., Ouchi 1979; Eisenhardt 1985). While output control requires the controlee to reach a certain goal or objective given by the controller in order to be rewarded, process control requires the controlee to adhere to specified procedures and routines during the process and doing so is rewarded. In contrast, informal control modes do not require specific incentives to align the goals of controller and controlee as shared norms and values exist (Kirsch et al. 2002). Within informal control, self and clan control have been distinguished (e.g., Ouchi 1979; Kirsch 1996). Self-control occurs when controlees define and monitor their own goals achievement and reward or punish themselves accordingly. Clan control is similar to self-control with the exception that a group of controlees, rather than an individual controlee, embrace the same values and commit to achieving group goals (Kirsch et al. 2002).

Though the concept of control originates from organizational theory, it has attracted considerable attention among IS scholars (e.g., Kirsch 1997; Kirsch et al. 2002; Tiwana and Keil 2009). Yet, it has only been applied in the context of platform ecosystems quite recently and with a strong focus on software-based ecosystems (e.g., Ghazawneh and Henfridsson 2013; Goldbach et al. 2014; Wareham et al. 2014). According to Tiwana (2015), the relevance of the mentioned formal and informal control mechanisms in this context is decreasing due to redundancy and costliness. For instance, process control is often obsolete in platform settings, as platform owners are ultimately interested in the finished complement and are not directly affected by costs complementors have to bear, because the relationship between the platform provider and complementors is not the classical principal-agent relationship (i.e., the complementor is not hired by the platform provider) (Tiwana et al. 2010). Furthermore, it has been argued that clan control requires a relatively stable ecosystem in terms of complementors and that formal and informal control mechanisms are *"less viable in loosely coupled organizational structures"* (Tiwana 2015, p. 4). Therefore, in loosely coupled ecosystems that exhibit high fluctuations in terms of the complementors, like mobile app and crowdfunding platforms do, the providers often focus their efforts with respect to control mechanisms on input control. Input control can be defined as the degree to which platform owners use predefined rules and policies to judge whether a compliment should be allowed into the platform (Cardinal et al. 2004; Tiwana et al. 2010). Although scant literature exists that considers input control in different forms and contexts (e.g., Snell 1992; Cardinal et al. 2004; Boudreau 2010; Liu et al. 2014), prior IS research has mainly focused on output, process, and clan control, overlooking the increasing relevance of input control (e.g., Kirsch et al. 2002; Choudhury and Sabherwal 2003).

Consequently, there are two gaps in the literature. First, the question of how the presence or absence of input control affects platform ecosystems in general and crowdfunding platforms in particular remains largely unexplored. Second, different configurations of control mechanisms in platform ecosystems have been mainly explored theoretically or in lab experiments and thus there is a lack of real-life cases and longitudinal studies in this context.

3.2.2 Crowdfunding

Crowdfunding, which builds on the broader concept of crowdsourcing (e.g., Poetz and Schreier 2012; Bayus 2013; Huang et al. 2014), 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 investors. Crowdfunding enables project creators to collect contributions from a large number of project backers through an open call, mostly on the internet, without standard financial intermediaries (Schwienbacher and Larralde 2012; Mollick 2014). Over the last few years, a variety of different crowdfunding platforms have emerged and four distinct models of crowdfunding have been distinguished: donation-based, reward-based, lending-based, and equity-based (Kuppuswamy and Bayus 2014). These four models mainly differ with respect to the return backers can expect from their contribution to a campaign, which can either be financial, materialistic, idealistic, or philanthropic in nature (Ahlers et al. 2015). In donation-based crowdfunding markets, for instance, backers can expect no tangible return and thus pledge for a campaign due to altruism and warm glow (Andreoni 2006). In comparison, equity- and lending-based crowdfunding markets offer financial returns for the backers, though these returns might not always be the central reason to invest (Allison et al. 2013). Finally, in reward-based crowdfunding, backers can expect a non-financial tangible benefit for their investment. 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 (Belleflamme et al. 2014). Previous research has found these rewards to be a central reason for backers to participate in reward-based crowdfunding (Kuppuswamy and Bayus 2014). 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.

Though research has been undertaken with respect to all four types of crowdfunding, the dynamics of reward-based and lending-based crowdfunding have received the most attention among researchers so far. Most of this prior work has been focused on identifying informational cues (i.e., signals) considered by backers when making investment decisions on crowdfunding platforms. In this respect, researchers highlighted the importance of geography (e.g., Agrawal et al. 2011; Lin and Viswanathan 2015), the project creator’s social network (e.g., Agrawal et al. 2010; Lin et al. 2013), electronic word-of-mouth (e.g., Thies et al. 2014), and social information on the platform (e.g., Kuppuswamy and Bayus 2014). Though all these papers offer valuable contributions, no prior work has provided insights into the effects changes in control mechanisms can have on the dynamics within crowdfunding platforms nor have the goals of the platform providers and the effects of their decision-making been considered. This study therefore is an initial step towards understanding these dynamics and the effects of a policy change in this context under conditions of a natural experiment.

3.3 Research Context

Our study focuses on Kickstarter, which is one of the leading reward-based crowdfunding platforms today. The platform empowers project creators to launch their campaigns and acquire funding, customers, and supporters from all over the world. Since its launch in 2009, 8.4 million people have pledged almost $1.7 billion, funding over 80,000 projects (Kickstarter 2016b). Prominent examples of projects that published their campaigns on Kickstarter include one of the first smartwatches called Pebble, which sold its one millionth watch in December

2014, a music player by Neil Young, a full-length movie by Zach Braff, and the Oculus Rift, a virtual reality head-mounted display, which was acquired by Facebook in 2014 for approximately $2 billion, less than two years after their Kickstarter campaign.

3.3.1 Economics of Reward-Based Crowdfunding

3.3.1.1 Goals of the Platform Provider, Project Creators, and Backers

A goal of every platform owner is to create and exploit as many monetization opportunities as possible (Claussen et al. 2013). As crowdfunding platform owners mainly generate revenue through transaction-based fees[3], managing the demand and the supply side is at the core of platform management. Since higher numbers of high-quality campaigns are attractive to backers, allowing more campaigns onto the platform seems beneficial for Kickstarter. In turn, a high number of campaigns might, however, represent an entry barrier for additional complementors (Hagiu 2011). Furthermore, as Kickstarter follows the all-or-nothing funding model, where only campaigns that reach their funding goal receive funds and thus generate revenue for Kickstarter, campaign quality and funding success are crucial. Thus, simply allowing more campaigns onto the platform might not yield any increase in revenue for the platform.

The goals of project creators, on the other hand, are more diverse. Most obviously, project creators try to gather as much funding as possible or as much as they require. Furthermore, 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 their idea. Hence, the campaigns themselves can also have a certain marketing effect for the respective project, as press attention potentially follows crowdfunding campaigns (Shane and Cable 2002; Burtch et al. 2013; Mollick 2014). Similar to early stage investors that, besides financial support, typically offer advice, governance, and prestige (Gorman and Sahlman 1989; Zimmerman and Zeitz 2002), crowdfunding communities also provide additional services to the creators, including mentorship to newcomers and feedback on the campaign presentation (Hui et al. 2014).

Though the rewards have been found to be a central reason for backers to participate in reward-based crowdfunding (Kuppuswamy and Bayus 2014), just like the rewards, the actual goals of backers can be extremely heterogeneous (Mollick 2014). Nevertheless, all campaign backers may be thought of as individuals making an investment decision based on their expectation for success and the appeal of the respective campaign (Agrawal et al. 2011). Previous research has shown that backers respond to signals of quality across all crowdfunding models and regardless of their expectations for tangible or financial returns (Mollick 2014; Burtch et al. 2015).

[3] When we refer to revenue, this only includes the transaction-based fees the crowdfunding platform charges.

3.3.1.2 Drivers of Campaign Success

Since investments in crowdfunding campaigns are highly uncertain, potential backers often need to make their investment decisions based on limited and potentially biased information provided by the project creator. Therefore, drivers of success for crowdfunding campaigns, such as quality signals, have been of great interest to scholars so far (e.g., Mollick 2014; Ahlers et al. 2015). The assumption is that these signals reveal the underlying quality of a project, ensuring that projects with a higher quality receive more funding compared to those with a lower quality (Mollick 2014). According to signaling theory, quality signals can only be credible if a project creator offering a low quality has higher costs acquiring them compared to a project creator offering a high quality (Spence 1973; Kirmani and Rao 2000; Connelly et al. 2011). Hence, prior to the policy change, being allowed to publish a campaign on Kickstarter could be considered a quality signal in itself, as passing the input control was a greater challenge for low-quality projects. As higher information asymmetry increases the relevance of quality signals, the omission of this inherent quality signal should increase the importance of the remaining signals. Thus, our goal is to assess the reaction of the crowd to the omission of the input control and to determine how the policy change affected the relative impact of the remaining quality signals on the backers' decisions to fund a campaign.

Mollick (2014) gave an early assessment of the role of quality in crowdfunding and identified several signals that influence campaign success. As crowdfunding offers a wide range of quality signals, we will present them in two stages. We first consider the level of preparedness of the creator as a signal of quality (Chen et al. 2009). Hence, we examine three signals that are determined before the campaign is launched on the platform. First, did the creator produce a video for his campaign? Uploading a video is strongly recommended by Kickstarter, claiming that campaigns that do not contain a video have a much lower success rate compared to those that do (Kickstarter 2016a). Second, we evaluate the preparedness by looking at the description length (DL) of the campaign, the underlying intuition being that a longer and more detailed description can reduce the information asymmetry better than a shorter description. Third, given that not only length but also the quality of the description serves as a signal, we checked for spelling errors (SE) as the lack of proofreading implies reduced preparedness and generally lower quality (Mollick 2014). To identify spelling errors, we matched the project description against the list of the 4,260 most commonly misspelled words in Wikipedia articles[4] (Wikimedia Foundation 2016).

Next, we turn to quality signals relevant during the funding period. Again, we use three quality signals that are based on prior research. First, another recommendation from the platform provider is to add *"updates that build momentum"* (Kickstarter 2016a). Furthermore, updates indicate a prepared creator (Mollick 2014) and also serve as a communication tool. Updates are often used to clarify certain aspects of the project and respond to frequent inquiries from the community. We therefore include the update frequency (UF) as a measure of quality.

[4] Words that could yield false positives (i.e., words that are correct in other contexts) were removed from the list.

Second, the success of social media led to a strong presence of what is referred to as social information in electronic markets, which has become an important signal for consumers to use for decision support. Qualitative (e.g., electronic word-of-mouth) as well as quantitative (e.g., download rankings) social information has been shown to affect consumer decision-making during online purchases (e.g., Chevalier and Mayzlin 2006; Duan et al. 2008b), helping them to overcome the information asymmetry for products whose value is difficult to ascertain before purchase (Akerlof 1970). In this regard, Thies et al. (2014) examined effects of social buzz on the likelihood of success of crowdfunding campaigns. Their findings show that social buzz (especially Facebook shares) positively influences campaign backing in the future. We therefore included Tweets on Twitter (TTW) and Facebook Shares (FBS) as quality signals.

As our final measure of quality, we employ a quality signal that cannot be altered by the project creators directly. Following Mollick (2014), we determined whether the project's campaign was a so-called *Staff Pick* (SP), meaning that the campaign was featured on Kickstarter's homepage and was added to a separate list of campaigns recommended by the platform. This special promotion offered by the platform itself is reserved for campaigns that are selected by Kickstarter staff because they are particularly compelling with respect to the video, description, rewards, or the project idea (Kickstarter 2016a).

3.3.2 Policy Change on Kickstarter

Project creators who are interested in publishing a campaign on Kickstarter have to go through a process of creating an account with the platform and then setting up their campaign by filling out an online form several pages long. To start a campaign, the project creator is then required to upload a photo, add a title and a description, outline the comprised rewards, and is encouraged to provide a campaign video and additional information. Once this process has been completed, the quality of the finished campaign is evaluated by Kickstarter staff based on a set of rules and policies defined by the platform. This formal input control applied by Kickstarter is rather unique in the context of reward-based crowdfunding, but regularly applied in software-based platform ecosystem such as Apple's App Store. Despite this control mechanism project creators had to subject themselves to, Kickstarter has become one of the leading crowdfunding platforms over the last few years. Still, creators of lucrative projects regularly decided to publish their campaign on a different platform such as Indiegogo after being rejected by Kickstarter due to the strict rules and policies (Jeffries 2014; Kelion 2014).

In June 2014, Kickstarter altered its strategy with respect to the control mechanisms by implementing a policy change regarding their approval process for campaigns that entailed two major changes (Strickler 2014). First, the control mechanisms the project creators had to subject themselves to prior to the change were replaced with an algorithm verifying that the campaign fulfills the basic requirements (e.g., has a description). Second, the previously elaborate list of rules and policies was reduced to only three rules, requiring campaigns to be shareable, honest, and within the confines of reward-based crowdfunding (Strickler 2014). Kickstarter announced this policy change with the following statement:

> *"We want creators to have the support and freedom they need when building their projects. That's why we're introducing a feature called Launch Now. It gives creators a simple choice: go ahead and launch your project whenever you're ready, or get feedback from one of our Community Managers first."* (Strickler 2014)

What motivated Kickstarter to implement such a major policy change and move from a curated to a more open platform despite its popularity and success? Though excluding low-quality campaigns from the platform is an error-prone and expensive process, moving from authority-based platform governance with rules and policies to a more trust-based governance that is based on the assumption that the controlee has a strong intrinsic motivation to reach the desired goal (i.e., a high-quality campaign) can, in fact, unbalance the ecosystem (de Reuver and Bouwman 2012). While it is likely that, after the policy change, an increasing number of campaigns will be published on the platform due to the removed control mechanisms, letting *a thousand flowers bloom* might have negative effects for the ecosystem. The uncontrolled variance in the quality of campaigns can lead to a situation where, ultimately, the platform provider has to bear the negative costs of the poor quality provided by the complementors (Wolter and Veloso 2008). For example, during the *Atari shock* in the 1980s, Atari's platform was flooded with low-quality video games due to its inability to control quality, which ultimately led to bankruptcy (Coughlan 2004). At the same time, platform ecosystems must employ mechanisms to leverage autonomy to complementors in order to generate a sufficient number of high-quality and innovative complements that foster user adoption and let the market determine winners and losers (Wareham et al. 2014).

As Kickstarter's policy change was not announced beforehand, giving backers as well as creators no time to adapt their strategies prior to the change, it can be assumed endogenous for the platform owner but exogenous for project creators and backers. This setting therefore offers a unique opportunity to examine how intentionally relinquishing control over a platform affects the dynamic relationship among the different stakeholders, which we examine in the remainder of this paper. To identify the dynamics caused by the policy change, we use descriptive as well as econometric evidence.

3.4 Data and Methodology

We collected a unique, daily time series dataset that covers the period from December 4th 2013 to December 3rd 2014, and contains a total of 67,384 Kickstarter campaigns that started within this timeframe. The policy change (PC) was enacted from 3rd of June onward, giving us 6 months of data before and after the policy change. We chose this time span to adequately control for seasonality and time trend effects. For each campaign, our dataset includes the start date and performance indicators such as the number of backers and the amount of funding the campaign received. Furthermore, we recorded indicators for the campaign's quality such as whether it contains a video, the length of the project description, social buzz, and update frequency.

Our data is suitable for our purposes for several reasons. First, this natural experiment-like change of control mechanisms allows for similar identification as for field experiments (Goldfarb and Tucker 2011; Tucker and Zhang 2011; Claussen et al. 2013). Second, we have data on campaigns before and after the policy change, which lets us isolate its effect. Third, as we have data on every campaign that ran on the platform in the specific period, we are able to avoid selection or survivor biases. Finally, Kickstarter is one of the most prominent crowdfunding platforms, making the results relevant for the entire industry.

Our applied research method is twofold. We first consider descriptive and illustrative evidence for the effects of the policy change on Kickstarter with regard to key metrics of the ecosystem. We then continue with a negative binominal regression (NB) to test how the rule change moderated the relative importance of the drivers of campaign success, measured by the total number of campaign backers. Variable definitions, abbreviations, summary statistics—before and after the policy change—and pairwise correlations for all numerical variables are given in Table 3-1 and Table 3-2. To check for robustness of our model results and to rule out alternative explanation for the observed effects of the policy change, we conducted a number of robustness checks that are described in detail in the respective section below.

3.4.1 Descriptive Evidence

We first look at the development of the ecosystem before and after the policy change based on the descriptive statistics. Given that the policy change is exogenous for project creators and backers, we can use this quasi-experimental setting to draw inferences from changes in numbers once the policy change (PC) is enacted. Since Kickstarter offers creators the opportunity to choose from eight different currencies, we converted all monetary values to USD based on the respective average exchange rate of 2014. Drawing from the numbers of Table 3-1, we observe a general decline of performance as well as quality indicators on the campaign level, while on the platform level a general increase of the key indicators is prevalent.

First, the average number of backers a campaign receives decreases by almost 40%. This decline is also mirrored in a decreased average funding of campaigns, formerly at almost $10,000, now plummeting to a mere $6,644. On the other hand, these declining numbers could be a result of the decline in quality, evident by the campaign's quality indicators and drivers of success. For instance, after the policy change, only 61% of all campaigns contained a video, down from 80%. Also, update frequency, description length and Facebook shares underwent a sharp decrease. The exceptions here are Twitter tweets and the percentage of campaigns that contained spelling errors. While tweets rose on average after the policy change, spelling errors declined, which is supposedly due to the shorter descriptions and the consequently lower susceptibility to spelling mistakes. The decreased percentage of campaigns that reach their funding goal further supports the argument for the declining average quality and the quick reaction of the crowd to the policy change.

Next, we take a closer look at the key indicators on a platform level. As mentioned before, the goal of the platform owner is to create monetization opportunities. While we observe a general decline in quality and funding on a campaign level, platform indicators suggest that the policy change indeed increased platform revenue, as the increased number of campaigns compensated for the lower average revenue per campaign. Still, the variance of the weekly revenue sharply increased, pointing towards less predictable revenue streams for the platform.

Table 3-1 Summary Statistics

Variable	Description	Total	Before PC	After PC	Change
		Mean (SD)			
Backers	Number of campaign backers	94 (678)	123 (884)	78 (524)	-37%
Pledged Amount	Amount the campaign accumulated in USD	$7,844 (77,486)	$9,942 (78,393)	$6,644 (76,938)	-33%
Pledge Goal	Target amount of the campaign in USD	$47,260 (1,197,845)	$33,174 (719,147)	$55,313 (1,399,756)	+67%
Duration	Funding duration in days	32.7 (11.1)	32.4 (10.7)	32.9 (11.3)	+2%
Staff Pick (SP)	Dummy is 1 if the campaign is a Staff Pick; 0 otherwise	0.11 (0.32)	0.12 (0.32)	0.11 (0.32)	-8%
Video	Dummy is 1 if the campaign contains a video; 0 otherwise	0.68 (0.5)	0.80 (0.4)	0.61 (0.5)	-24%
Description Length (DL)	Length of the campaign description in characters	3,512 (3,748)	3,998 (3,807)	3,234 (3,685)	-19%
Spelling Errors (SE)	Dummy is 1 if the description contains error(s); 0 otherwise	0.07 (0.25)	0.07 (0.25)	0.06 (0.24)	-3%
Update Frequency (UF)	Number of daily updates the creator posts	0.14 (0.28)	0.18 (0.34)	0.11 (0.23)	-39%
Facebook Shares (FBS)	Number of Facebook shares the campaign received	325.29 (4,463)	374.30 (6,033)	297.28 (3,242)	-21%
Twitter Tweets (TTW)	Number of tweets on Twitter the campaign received	81.7 (646.9)	76.5 (667.6)	84.7 (634)	+11%
Success Rate	Percentage of campaigns that reach their pledge goal	0.33 (0.47)	0.42 (0.49)	0.29 (0.45)	-31%
Account Age	Days between account creation and start of campaign	262 (379)	278 (367)	252 (385)	-9%
Platform Revenue per Campaign	5% commission for successful campaigns	$342 (3,865)	$437 (3,906)	$288 (3,779)	-34%
Weekly Platform Revenue	Average weekly revenue	$480,524 (190,879)	$444,663 (156,406)	$501,026 (205,242)	+13%
Total Platform Revenue	Cumulative revenue during observational period	$2.31e+07	$1.07e+07	$1.24e+07	+16%
N per Day	New campaigns per day	242.7 (9.5)	163.0 (53.2)	288.4 (127.7)	+77%
Observations	Number of campaigns	67,384	24,511	42,873	+75%

To further illustrate this development, Figure 3-1 shows the average number of new campaigns on Kickstarter during our observational period. The underlying data for Figure 3-1 and Figure 3-2 was averaged on a weekly level as well as the 6-month period before and after the policy change to create a clearer representation. We observe that prior to the policy change, the number of new campaigns was significantly lower and underwent a sharp increase shortly after the enactment. Figure 3-1 also plots the average revenue the platform generates with a single campaign during our observational period. Here, we notice the sharp decline after the policy change. Two distinctive effects of the policy change are shown in Figure 3-1. First, the removal of the entry barrier enabled more project creators to publish their campaign on the platform, increasing the variety of choice for potential backers. On the other hand, as the number of campaigns rose, the average funding per campaign declined. This indicates that the increased absolute number of campaigns was not necessarily accompanied by an increased absolute number of backers.

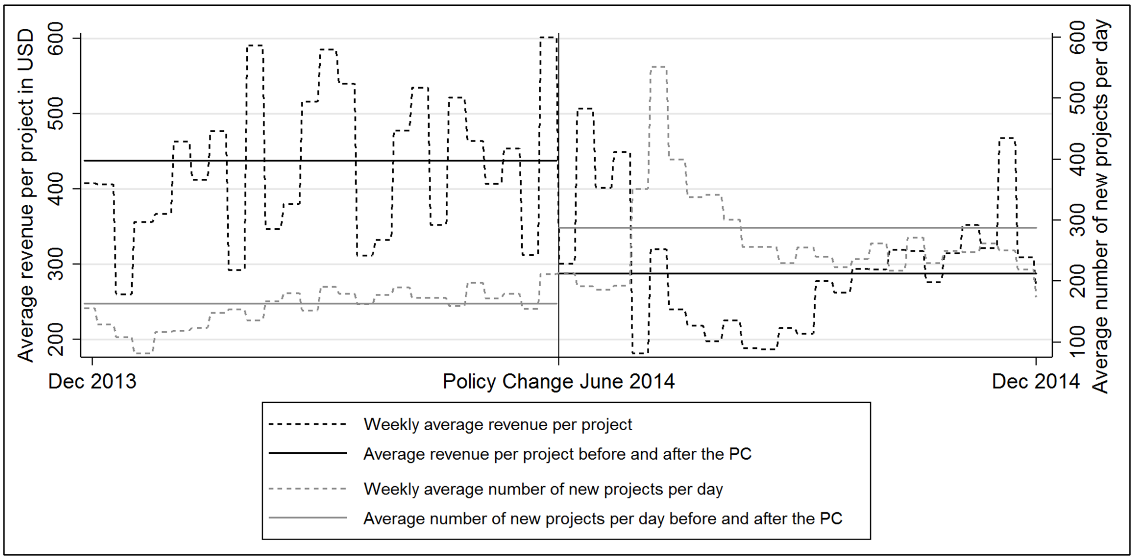

Figure 3-1 Effects of the Policy Change on Count and Revenue of Campaigns

Figure 3-2 combines the two graphs from Figure 3-1 and plots the total weekly revenue as well as the average of the average before and after the policy change against the start date of the respective campaigns. We identify a small increase in weekly platform revenue. However, the increased revenue is accompanied by an increased variance of it, making it less predictable, and suggesting a development towards a more blockbuster-based ecosystem (Rosen 1981). This is also reflected by the platform revenue of $664,261 that was generated with the campaign of *The Coolest Cooler* that started shortly after the policy change.

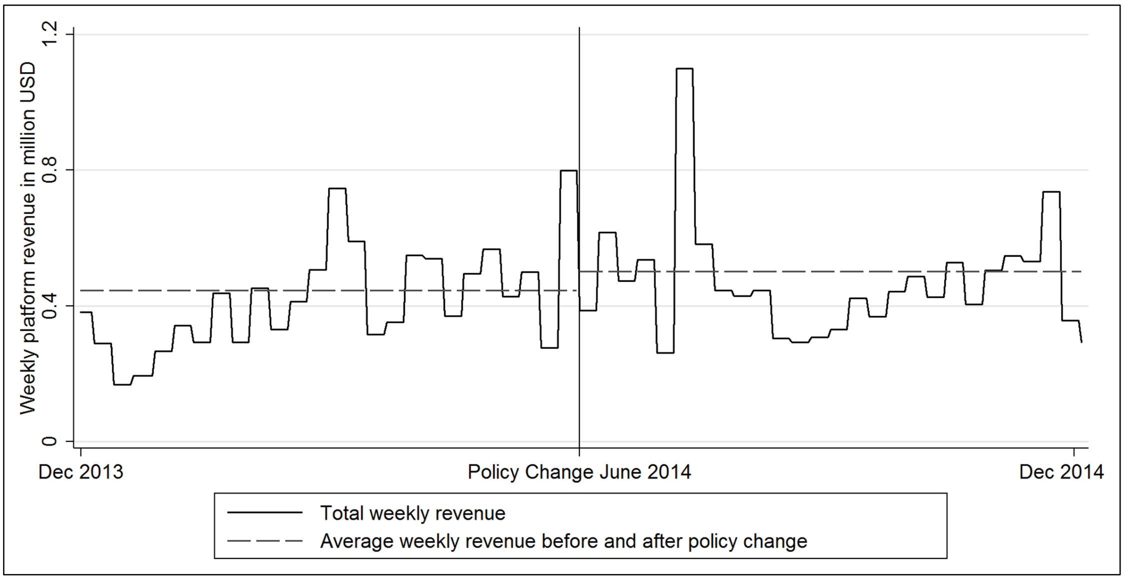

Figure 3-2 Effects of the Policy Change on Platform Revenue

Overall, we see a decline in average campaign quality (i.e., fewer updates, fewer videos, shorter descriptions), as well as higher and allegedly more unrealistic funding goals and a decreased success rate. Still, the numbers also suggest higher total revenues for the platform provider when looking at the absolute numbers, which denotes that the higher number of campaigns compensated the lower success rate and average funding amount per campaign. A possible explanation for the decline in quality could be the time creators invest on the platform before starting their campaign. Creators that familiarize themselves with the platform longer can be expected to contribute a more appealing campaign. We therefore looked at the account age of creators and witness a strong decline in the average number of days an account exist before the campaign is launched. Furthermore, after the policy change, almost 25% of all creator accounts have been in existence for a week or less before their campaign launched, up from 13%. It could be argued that these inexperienced and hasty project creators are a major driver of the decline in campaign quality. To further deepen our understanding of the implications of the policy change, especially for project creators and backers, we will now turn to our econometric analysis.

3.4.2 Econometric Evidence

Our econometric analysis focuses on the effects of the policy change for the drivers of success for crowdfunding campaigns. To do this, we employ a negative binominal regression (NB) to test how the rule change affected the drivers of campaign success and their signaling effects on prospective backers' pledge behavior by using the number of backers as our dependent variable. We chose the number of backers as our main proxy for success as we are more interested in the actual backer's decision of whether to fund the project or not, instead of in the absolute investment amount, especially as the individual funding amount is strongly driven by the material rewards offered by the project creator. Still, the correlation between backers and funding amount is relatively high, which makes it possible to infer the overall success of a campaign from the number of backers.

We use a robust negative binominal regression instead of a Poisson regression as our dependent variable is a significantly overdispersed count variable (Long 1997; Cameron and Trivedi 2005) and the equidispersion restriction of the Poisson model is relaxed here (Greene 2008). Still, all results are robust to the Poisson specification. Our model is then formalized as follows:

$$E\left[y_i \middle| x_i, \varepsilon_i\right] = \exp\left(\alpha + x_i\beta + \varepsilon_i\right)$$

where y_i denotes the number of backers, x_i represents project specific independent variables and control variables, while ε_i acts as the error term.

Table 3-2 Pairwise Correlations for Numerical Variables

		1	2	3	4	5	6	7	8	9	10	11
1	Backers	1.00										
2	Duration	0.00	1.00									
3	LN (Pledge Goal)	0.10*	0.21*	1.00								
4	Staff Pick	0.16*	-0.03*	0.11*	1.00							
5	Video	0.08*	-0.02*	0.23*	0.20*	1.00						
6	LN (Description Length)	0.13*	0.01	0.31*	0.23*	0.38*	1.00					
7	Spelling Errors	0.01*	0.02*	0.05*	-0.00	0.01*	0.012*	1.00				
8	Update Frequency	0.22*	-0.15*	0.04*	0.26*	0.22*	0.31*	0.02*	1.00			
9	LN (Facebook Shares)	0.20*	0.00	0.21*	0.33*	0.43*	0.40*	-0.00	0.38*	1.00		
10	LN (Twitter Tweets)	0.22*	0.01*	0.24*	0.34*	0.35*	0.39*	0.01*	0.40*	0.71*	1.00	
11	Policy Change (PC)	-0.03*	0.02*	-0.05*	-0.01	-0.20*	-0.15*	-0.01	-0.12*	-0.09*	-0.04*	1.00

Note: *t statistics are omitted for brevity. * p < 0.05.*

We included several controls in our model to account for alternative explanations. All numerical variables and their correlations are given in Table 3-2. First, we used a category dummy for all 15 project categories on Kickstarter, ranging from art to film, fashion, music, and technology. We further implemented a time dummy for each month to control for possible seasonality effects and the general growth trend of crowdfunding platforms. Additional controls are the campaign duration to account for the exposure length and the natural logarithm of its funding goal. Our baseline model (1) furthermore includes all aforementioned drivers of success, including the description length, update frequency, and social buzz measures. We then added the dummy variable PC in model 2 to indicate the policy change. The dummy turns from 0 to 1 if the campaign started after the input control was revoked. In order to model the moderating effect of the policy change on the relationship between project success drivers and campaign backing, we then subsequently include all potential drivers of project backers as main effects as well as in interaction terms with the rule change in models

(3) to (7). The interaction term then lets us discern if each quality indicator became a more important driver of success after the policy change. Respectively, if the signaling power of the alterable signal was enhanced after the inherent quality signal was attenuated.

Table 3-3 Negative Binominal Regression on Campaign Backing

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Category (Control)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month (Control)	YES	YES	YES	YES	YES	YES	YES	YES	YES
Duration	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
LN (Pledge Goal)	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*
Staff Pick	0.53***	0.53***	0.39***	0.53***	0.53***	0.53***	0.52***	0.52***	0.52***
Video	0.35***	0.34***	0.34***	0.19***	0.34***	0.34***	0.34***	0.32***	0.33***
LN (Description Len.)	0.14***	0.14***	0.14***	0.14***	0.1***	0.14***	0.14***	0.13***	0.14***
Spelling Errors	-0.18***	-0.18***	-0.18***	-0.18***	-0.18***	-0.17***	-0.18***	-0.18***	-0.18***
Update Frequency	2.37***	2.34***	2.35***	2.35***	2.35***	2.34***	1.99***	2.35***	2.36***
LN (Facebook Shares)	0.39***	0.4***	0.4***	0.4***	0.4***	0.4***	0.4***	0.33***	0.4***
LN (Twitter Tweets)	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***	0.11***
Policy Change (PC)		-0.89***	-0.92***	-1.06***	-1.33***	-0.89***	-1***	-1.23***	-0.99***
PC x Staff Pick			0.22***						
PC x Video				0.23***					
PC x LN (DL)					0.06***				
PC x Spelling Errors						-0.01			
PC x Update Frequency							0.77***		
PC x LN (FBS)								0.12***	
PC x LN (TTW)									0.07***
BIC	533,904	533,469	533,412	533,367	533,429	533,481	533,183	532,519	533,259
Log Likelihood	-266,752	-266,529	-266,495	-266,472	-266,503	-266,529	-266,380	-266,049	-266,418
chi2	70,292	70,508	71,528	70,439	70,463	70,516	72,647	71,993	72,271
N	67,384	67,384	67,384	67,384	67,384	67,384	67,384	67,384	67,384

Note: *t statistics are omitted for brevity. A constant is calculated but not reported. * p <0 .05, ** p < 0.01, *** p < 0.001.*

Based on the results of the model (2) in Table 3-3, we can confirm the conclusion drawn from our descriptive evidence that the policy change caused a decline in the number of backers. The policy change decreases the number of backers by a factor of 0.59, with all other variables held constant. We calculated this incidence rate ratio from exponentiating the policy change variable's coefficient (Long 1997). Incidence rate ratios for other variables were calculated in the same way. In the subsequent models, we see that quality indicators generally became more important after the policy change, indicated by the positive and significant coefficients of the interaction terms in models (3) to (7). The positive effect of being a Staff Pick from the platform or having a video increased by a factor of 30%, while the importance of the description length only increased by about 10%. The exception here is spelling errors, which did not increase in signaling strength. Still, it is the only negative signaling in our analysis. The biggest gain in explanatory power compared to the baseline model, indicated by the lower BIC, was achieved in models (7) through (9), which incorporated the interaction terms with update frequency, Facebook shares, and Twitter tweets highlighting the increased importance of social buzz and community interaction after the policy change. Here, the signaling effect of Twitter tweets as well as Facebook shares became, again with all other variables held constant, approximately 10% stronger.

In summary, we have gathered strong evidence that the rule change indeed incentivized creators to publish lower quality campaigns on the platform as the input control mechanism was removed. On the other hand, the increased number of campaigns compensated for the lower quality with regard to platform revenue by sheer volume. Additionally, we found strong empirical evidence that the removal of an important quality signal encourages users to put more emphasis on the remaining quality indicators.

3.4.3 Robustness Checks

To check for the robustness of our models, we conducted six sets of robustness checks. All tests resulted in similar significance levels and identical directions of all relevant coefficients. First, we ran an OLS regression with the natural logarithm of the monetary project funding as the dependent variable. Second, we implemented a dummy variable that turned to one if the campaign reached or exceeded its funding goal. We then ran a probit regression with this dummy as the dependent variable to further validate our results. Third, we also ran a Poisson regression with the original specification, again resulting in the same directions and significance of all relevant coefficients. Fourth, we excluded all campaigns whose funding period coincided with the policy change. Fifth, as Kickstarter removed a number of rules on the same date the policy change was enacted and therefore allowed certain projects onto the platform after the policy change that were previously prohibited, we excluded all campaigns that would not have been possible prior to the policy change based on the subcategories they were listed in for a further robustness check. Furthermore, in the weeks following the policy change, Kickstarter added two new campaign categories to the website, namely, *Crafts* and *Journalism*. For a further robustness check, we also removed all campaigns from our analysis that were listed in these two categories. Finally, we shrank the observed time period around the policy change by moving to a time window first from 12 to 6 months and then down to 3 months. Specifications show that our results persist over these shorter time frames as well. In order to control for rival explanations, we included control variables in our main regression as well as in all other robustness checks, including campaign categories, general time trends, campaign durations, and funding goals. All of our results can therefore be considered to be robust with regard to alternative explanations and campaign success measurements.

3.5 Discussion

Our analysis of the policy change on Kickstarter with respect to the abolishment of input control yielded several interesting results. Corresponding to our first research question, we find that the policy change had a profound impact on each of the platform's stakeholders and the dynamic relationships among them. According to the announcement published by Kickstarter to explain and justify the policy change, one of the main goals was to allow *"more diverse ideas to thrive on Kickstarter" (Strickler 2014)*. While our results show that this goal was achieved with an increase of 77% in the number of new campaigns per day after the policy change, it is accompanied by a decrease in average campaign quality. We see that, as a reaction to the policy change, almost all quality signals that can be influenced directly (e.g., campaign video) or indirectly (e.g., Facebook shares) by the project creator see a strong decrease. It thus seems that the screening process was not automatically substituted by any informal control mechanism such as clan or self-control that would have encouraged project creators to define and monitor their own goals or embrace group values and therefore commit themselves to higher quality campaigns. This is not surprising, as posting a campaign on the platform is not a long-term commitment for project creators and Kickstarter therefore does not provide a stable ecosystem in terms of complementors, which is required to deploy clan control (Ouchi 1979). Kickstarter recently started trying to prolong the relevance of the platform for project creators with a new feature called *Spotlight*, which turns every successful campaign into a showcase and web shop for the respective project (Kickstarter 2015c). This might be a first attempt to establish a shared vision for the platform among the different stakeholders. Currently, however, Kickstarter leaves the complementors broad latitude to decide what and how they want to contribute to the platform, which makes it difficult to ensure coordination (i.e., who contributes what campaigns) and task completion (i.e., publishing high-quality campaigns), since leaving the platform is as easy as joining (Gulati et al. 2012, p. 576). Our results confirm this, as we see that after the policy change, the project creators publish their own campaign more quickly after creating their account with the platform, meaning that they invest less time to familiarize themselves with the platform and possible success factors.

For our second research question, we examined how the drivers of campaign success were affected by the policy change. We find that after the policy change, all of the inspected quality signals—with the exception of the absence of spelling errors—became more important for the potential backers' evaluation of campaigns. This effect was to be expected, as being able to publish a campaign on Kickstarter is not a valid quality signal in itself anymore. Considering this and the decrease in campaign quality, it is not surprising that we see a lower average success rate after the policy change and a widening gap between the project creators' expectations (pledge goal) and the amount their campaigns eventually accumulate (pledged amount). Though this means that, on average, individual campaigns generate less revenue for the platform provider, also making the platform less lucrative for complementors, the data shows that this drop is compensated for by the increase in the number of campaigns.

While the true intentions behind the policy change remain hidden, exploiting as many monetization opportunities as possible is at the core of platform management (Claussen et al. 2013). Even though this goal was therefore achieved with the policy change, we see that, due to Kickstarter's all-or-nothing funding model, the apparent increase in platform revenue is more dependent on fewer blockbuster campaigns, evident by the rise in market concentration towards a smaller percentage of campaigns that gather most of the funding. Though relinquishing control over the platform should help turn Kickstarter into a *long tail* market, where niche complements contribute substantially to the platform's revenue due to their sheer volume (Anderson 2006; Elberse 2008), the platform provider inhibits this development through the all-or-nothing funding model, which is not compulsory on the platform of Kickstarter's strongest competitor Indiegogo.

3.5.1 Theoretical Contributions

Our study makes three important contributions to the IS control literature and to the emerging research on platform ecosystems. First, previous IS control studies have focused almost exclusively on output, process, and clan control, but inadvertently neglected input control (e.g., Kirsch et al. 2002; Choudhury and Sabherwal 2003). Ours is one of the first studies to conceptualize and examine input control as a formal control mechanism and to show how its abolishment affects critical performance indicators on platforms, such as financial performance and project diversity as well as end-user and complementor participation. As a result, we were not only able to analyze the impact of the input control change on an aggregate platform level, but also on a more granular level for different platform stakeholders. Our study thus complements previous IS control studies and demonstrates that input control (or the lack thereof) can have tremendous financial and behavioral effects on platforms. Second, we add to the growing stream of research on the implications of policy changes on platform ecosystems (e.g., Claussen et al. 2013; Burtch et al. 2015) by showing how adjusting a critical platform governance mechanism can affect an entire platform ecosystem and what dynamics unfold on the part of the different stakeholders. To the best of our knowledge, our study is also the first in a crowdfunding ecosystem to examine the effects of a sophisticated control change under conditions of a natural experiment. We believe, however, that our insights are not strictly limited to this context, as input control mechanisms are a ubiquitous phenomenon in platform ecosystems overall. Finally, and more broadly, our study also shows that policy changes can have significant effects on platform signaling, by demonstrating that changes in platform governance mechanisms can significantly shift the relative importance of signals for platform users and have considerable consequences for the overall dynamics among platform stakeholders. As such, our findings highlight that quality signals (i.e., users' decision cues) on platforms are fragile and vulnerable to (internal and external) shocks rather than static and stable over time.

3.5.2 Practical Implications

Beyond the theoretical contributions of this paper, we also see a variety of practical implications that should be considered by the providers of crowdfunding platforms and project creators.

3.5.2.1 Providers of Platform Ecosystems

For the providers of platform ecosystems, it is important to realize that changes in governance mechanisms can have a substantial influence on decision-making processes of users and complementors. It is therefore crucial for the platform providers to develop a deep understanding of the complementors' (project creators') goals, strategies, and capabilities that might be affected by any policy changes and of any potential areas of conflict that might arise (Yoffie and Kwak 2006). For example, after the policy change, Kickstarter attracted a number of campaigns likely to be hoax that may be seen as a form of rebellion against the new relaxed policies (Lecher 2014).

Prior research has found that it is a managerial challenge to exercise enough control over a platform to ensure integrity while relinquishing enough control to encourage innovation (e.g., Boudreau 2010; Tiwana et al. 2010; Boudreau 2012; Tiwana 2015). In this respect, platform providers can either enact *hard* input control mechanisms based on rules and policies or incentivize complementors through *soft* stimuli. Though Kickstarter became successful before the policy change despite the screening process and managed to provide a high average campaign quality due to this mechanism, such mechanisms can also *"be counterproductive in a nascent market in which consumer preferences are not (yet) settled"* as innovative complements might fail to comply with any established criteria (Claussen et al. 2013, p. 199). Though the platform's rising revenue seems to confirm that the decision to abolish input control was the appropriate approach for Kickstarter, the decreasing average campaign quality suggests that the policy change has the potential to backfire in the long run. The platform provider should employ other, soft mechanisms to encourage project creators to contribute higher quality campaigns in the future. Facebook, for instance, managed to increase the average quality of third party apps offered on the platform by rewarding highly engaging apps with further opportunities to engage users (Claussen et al. 2013). Though Kickstarter offers a similar mechanism with the so-called *Staff Picks*, there is no clear and democratic path to becoming featured by Kickstarter that would ensure equal access for every project creator and motivate them to invest in higher quality campaigns (cf., Kickstarter 2015b).

3.5.2.2 Project Creators

For project creators, the easier access to the platform seems attractive, but goes along with stronger competition due to the increased number of rival campaigns. Though crowdfunding campaigns on Kickstarter are most often unique and therefore do not compete for backers directly, each campaign has to compete with all other campaigns running at the same time for the attention of the prospective backers browsing Kickstarter. This is particularly true within the distinct categories (e.g., technology or design) that are used on the platform to sort and rank campaigns. Furthermore, being able to publish a campaign on Kickstarter could previously be regarded an important and inherent quality signal, which no longer exists after the policy change. This further increases the competition for project creators with campaigns on other platforms. Consequently, the policy change increases the focus on the quality of individual campaigns and on the ability of the project creators to raise the awareness for their campaigns (e.g., through marketing), as the market solely determines winners and losers after the policy change and the increased number of campaigns makes it more difficult for the project creators to stand out of the crowd.

3.5.2.3 Backers

After the policy change, prospective backers have more choice, which possibly attracts individuals who previously did not participate in crowdfunding. On the other hand, this goes along with increased search costs and information asymmetry (Bakos 1997), as being able to publish a campaign on the platform is not a valid quality signal in itself anymore and backers therefore have to consider other quality signals in order to evaluate whether to pledge for a specific campaign. Our results confirm this, as we were able to show that due to the policy change, backers shifted their attention to other prevalent quality signals such as social buzz.

3.6 Limitations, Future Research, and Conclusion

While our study provides important insights and contributions to both research and practice in the context of platform ecosystems and control mechanisms, it is exploratory in several respects and we acknowledge certain limitations that need to be considered when interpreting the results and implications. First, our data is aggregated on a campaign level, meaning that we can only observe the aggregate behavior of backers and not the choices made by individuals. Furthermore, our data did not allow us to compare the characteristics of backers (e.g., demographics) before and after the policy change. Future studies could therefore focus on the backers' perspective to determine how the abolishment of input control mechanisms and the subsequent increase in variation and decrease in quality of a platform's complements influences decision-making on an individual level. Second, though we study one of the most prominent crowdfunding platforms, we only observe a specific time frame in its evolution within a still young and very dynamic market. Therefore, one should be cautious when extrapolating our findings to other, more mature platform ecosystems. Third, even though we deliberately chose to observe a rather long period before and after the policy change to avoid focusing on short-term dynamics, it remains unclear how long the measured effects persisted after the abolishment of the input control mechanisms. Finally, input control mechanisms are just one of multiple ways platform providers can relinquish or exercise control over complementors. Nevertheless, we believe that our study offers unique insights into the various effects and dynamics a platform owner can provoke when altering control mechanisms.

In conclusion, our overarching finding is that Kickstarter's policy change regarding the abolishment of input control was a double-edged sword for the platform's ecosystem. On the one hand, it increased the number and variety of campaigns, which is in line with the platform provider's expectation and might attract a higher number of backers in the future, therefore increasing platform revenue and prominence. On the other hand, the benefit of the increased number of campaigns is diminished, as Kickstarter's all-or-nothing funding model mitigates the marginal utility of additional campaigns. Furthermore, Kickstarter might lose its distinct status as a high-quality crowdfunding platform due to the decreasing average quality and success rates. Prospective project creators might therefore turn to rival platforms with more attractive funding conditions in the future.

This study contributes to the emerging literature on governance strategies for platform ecosystems and the role of input control in this context. We hope that our results provide impetus for further analysis of governance strategies for loosely coupled platform ecosystems and give actionable recommendations to platform providers and project creators in the crowdfunding context.

4 Dynamic Interplay of Social Buzz and Contribution Behavior

Title

Understanding the Dynamic Interplay of Social Buzz and Contribution Behavior within and between Online Platforms – Evidence from Crowdfunding[5]

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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

[5] This paper was awarded *Best Conference Paper Runner-Up* at the International Conference on Information Systems (ICIS 2014).

4.1 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; 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. 2011a) 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, 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 the 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.

4.2 Theoretical Background

4.2.1 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 (Shane and Cable 2002; Burtch et al. 2013; Mollick 2014).

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. 2015). 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.

4.2.2 Electronic Word-of-Mouth

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 and Reingen 1987; Brown et al. 2007). 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 (Schwienbacher and Larralde 2012; Belleflamme et al. 2014; Mollick 2014). 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.

4.3 Research Model and Hypotheses Development

In this section, we develop the theoretical rationale for our proposed research model. As shown in Figure 4-1, 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.

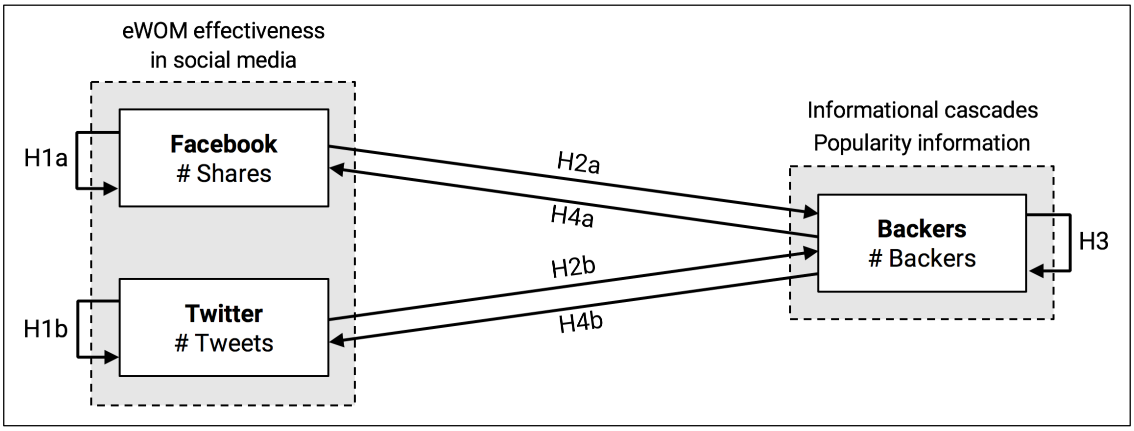


Figure 4-1 Research Model

4.3.1 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 for reflecting positively on the sender when shared via social media. Second, since a high perceived risk when a making purchase or investment decision 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., Liu 2006; Dhar and Chang 2009) 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 (Granovetter 1973; Chu and Kim 2011). 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.

4.3.2 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; 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. 2011a; 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.

4.4 Research Methodology

4.4.1 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. 2015).

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,

$$\begin{bmatrix} backers_t \\ facebookshares_t \\ tweets_t \end{bmatrix} = \sum_{j=1}^{J} \begin{bmatrix} \beta_{11}^{t-j} & \beta_{12}^{t-j} & \beta_{13}^{t-j} \\ \beta_{21}^{t-j} & \beta_{22}^{t-j} & \beta_{23}^{t-j} \\ \beta_{31}^{t-j} & \beta_{32}^{t-j} & \beta_{33}^{t-j} \end{bmatrix} \begin{bmatrix} backers_{t-j} \\ facebookshares_{t-j} \\ tweets_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{backers,t} \\ \varepsilon_{facebookshares,t} \\ \varepsilon_{tweets,t} \end{bmatrix} \qquad (1)$$

where $backers_t$, $facebookshares_t$ and $tweets_t$ denote daily project funders, shares on Facebook and tweets on Twitter. The number of backers of a project ($backers_t$) 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 the Akaike 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, of 1 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.

4.4.2 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 15, 2013 to March 24, 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 4-1 Summary Statistics

	Total	**Winner**	**Loser**	**Creative (Winner)**	**Social (Winner)**	**Entrepreneurial (Winner)**
	Mean (SD)					
Backers	46.36 (289.35)	83.31 (542.10)	32.17 (48.49)	103.99 (758.31)	56.28 (100.52)	95.68 (177.42)
Facebook (#Shares)	245.58 (443.38)	281.45 (595.01)	231.80 (368.13)	292.20 (656.25)	251.85 (524.58)	366.92 (532.18)
Twitter (#Tweets)	26.59 (151.85)	29.06 (201.18)	25.64 (127.97)	32.08 (184.94)	25.01 (233.20)	31.37 (89.04)
Received Funding	$3,465 ($13,696)	$6,001 ($27,717)	$2,491 ($4,659)	$7,007 ($28,795)	$4,709 ($21,096)	$6,489 ($11,173)
N (Projects)	6,340	1,759	4,581	877	737	145

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 life cycle (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 4-1 for the full dataset and each subsample.

4.5 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 4-2 and indicate that all of the variables are indeed stationary.

Table 4-2 Phillips-Perron Unit Root Test

	P-Statistic: Inv. Chi^2	**p-Value**
Backers	1.33e+05	0.0000
Facebook (#Shares)	1.67e+05	0.0000
Twitter (#Tweets)	1.44e+05	0.0000

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 4-3 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 fully dynamic system through PVAR analysis (Trusov et al. 2009).

Table 4-3 Granger Causality Tests

	Backers	**Facebook**	**Twitter**
Backers	-	43.46 (0.001)	9.05 (0.01)
Facebook (#Shares)	8.43 (0.01)	-	13.15 (0.001)
Twitter (#Tweets)	8.89 (0.01)	21.85 (0.001)	-

Note: *The results reported are CHI^2 statistics with p-values in parentheses. Granger causality tests are performed with 1 lag for consistency with the PVAR Models (as selected by AIC).*

4.6 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 4-4. 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 4-4.

Table 4-4 PVAR Results for Split-Sample Analysis

	Total	**Winner**	**Loser**	**Winner: Creative**	**Winner: Social**	**Winner: Entrepreneurial**
Response to:	Response of dependent variable: **Backers**					
Backers$_{-1}$	0.556***	0.514***	0.922***	0.484***	0.899***	0.892***
Facebook$_{-1}$	0.052***	0.094***	0.001	0.125***	0.002	0.015***
Twitter$_{-1}$	-0.002	-0.071*	0.001	-0.255***	0.001	-0.083***
Response to:	Response of dependent variable: **Facebook**					
Backers$_{-1}$	-0.200***	-0.218***	-0.016	-0.243***	0.069	-0.053
Facebook$_{-1}$	0.951***	0.968***	0.926***	0.997***	0.883***	0.950***
Twitter$_{-1}$	0.002	-0.032	0.002	-0.114*	-0.025	-0.147*
Response to:	Response of dependent variable: **Twitter**					
Backers$_{-1}$	-0.053**	-0.048*	0.034***	-0.067***	0.197***	0.013
Facebook$_{-1}$	0.006*	0.001	0.001	0.016**	-0.066***	0.009*
Twitter$_{-1}$	0.898***	0.855***	0.904***	0.906***	0.765***	0.753***

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 4-4 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 (Roberts 1984; Andreoni 1990), 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 backers seek feedback from their peers before supporting creative projects, while social and entrepreneurial campaigns do not require this evaluation process.

4.6.1 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 4-4 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 the classic literature on the bystander effect and public goods (Fischer et al. 2011).

Table 4-5 Variance Decomposition of Backers

Full dataset				Creative			
Days ahead	Backers	Facebook	Twitter	Days ahead	Backers	Facebook	Twitter
7	95.5%	4.5%	0%	7	96.1%	1.3%	2.6%
14	92.1%	7.9%	0%	14	92.8%	2.6%	4.6%
21	91.1%	8.9%	0%	21	91.7%	3.0%	5.3%
28	90.7%	9.3%	0%	28	91.3%	3.1%	5.6%
Winner				**Social**			
Days ahead	Backers	Facebook	Twitter	Days ahead	Backers	Facebook	Twitter
7	95.6%	4.1%	0.3%	7	99.9%	0.1%	0.0%
14	92.5%	7.1%	0.4%	14	99.8%	0.2%	0.0%
21	91.4%	8.2%	0.4%	21	99.7%	0.3%	0.0%
28	91.1%	8.5%	0.4%	28	99.7%	0.3%	0.0%
Loser				**Entrepreneurial**			
Days ahead	Backers	Facebook	Twitter	Days ahead	Backers	Facebook	Twitter
7	99.96%	0.03%	0.0%	7	97.0%	1.4%	1.6%
14	99.9%	0.1%	0.0%	14	93.7%	3.7%	2.6%
21	99.8%	0.2%	0.0%	21	91.6%	5.5%	2.9%
28	99.7%	0.3%	0.0%	28	90.5%	6.5%	3.0%

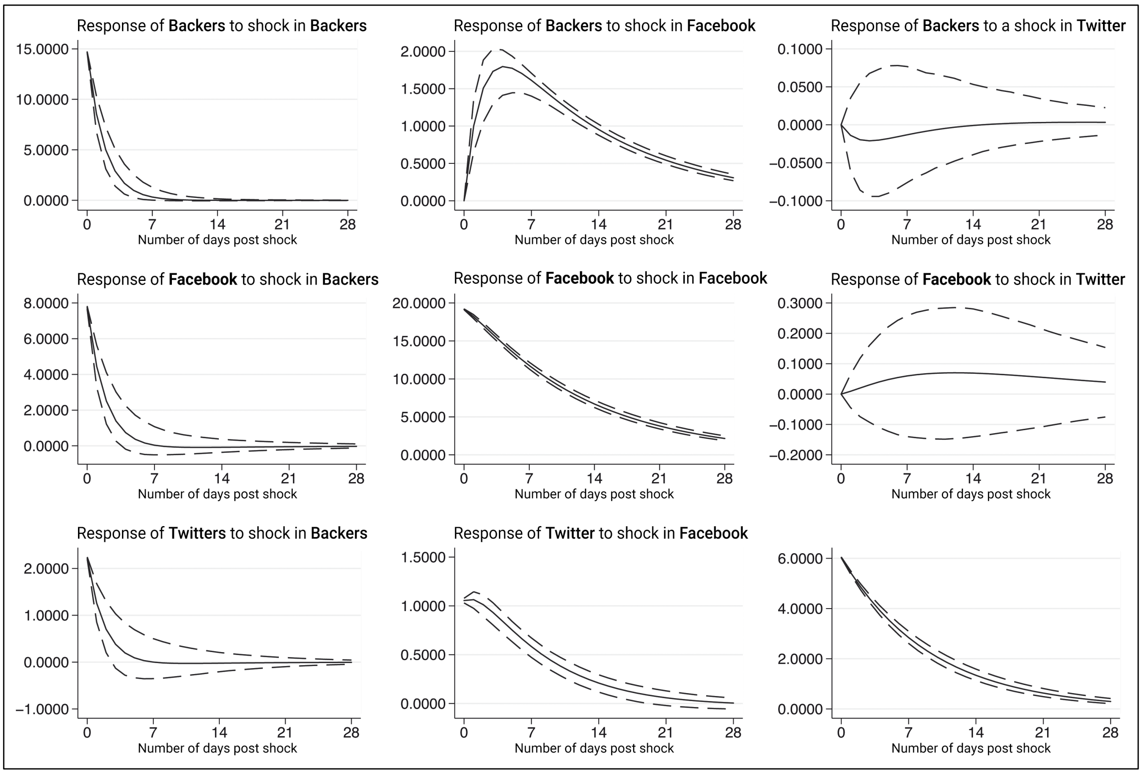
Note: *Percent of variation in the backer variable explained by column variable (7, 14, 21, and 28 days ahead) for each subsample and main regression.*

Finally, we also present the results of a variance decomposition analysis in Table 4-5, 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 of the dependent variables 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.

4.6.2 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 4-2. 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 $backers_{t-1}$ on $backers_t$, which attenuates rather quickly, while the response of $backers_t$ 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 $backers_{t-1}$ are very powerful in the short run but also decline extremely fast.



Note: *Errors are 5% on each side generated by Monte-Carlo with 1,000 repetitions*

Figure 4-2 Impulse Response Functions: Responses to Intra- and Cross-Platform Shocks

4.7 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 inverse 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.

4.7.1 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.

4.7.2 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.

4.7.3 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.

5 Emergence and Effects of Fake Social Information

Title

The Emergence and Effects of Fake Social Information: Evidence from Crowdfunding[6]

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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.

Keywords

Fake social information, perceived quality, signaling, crowdfunding, Facebook Likes

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5.1 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 (Pavlou et al. 2007). Specifically, qualitative social information such as customer product reviews as well as quantitative social information such as product ratings and download rankings have been shown to affect consumers' decisions when making online purchases (e.g., Chevalier and Mayzlin 2006; Duan et al. 2008b), helping them to overcome the information asymmetry for products whose quality is difficult to ascertain before purchase (Akerlof 1970).

An extremely widespread method to reflect consumer opinions in a quantitative manner is the use of social media buttons such as the Facebook Like button, which is present on about 30% of the most popular websites worldwide (Built With 2014). When placed on a website, the button shows a counter reflecting the number of Facebook users who have previously *"liked"* this specific web page or have shared the link to it with their peers. For subsequent visitors to the web page, 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., Duan et al. 2009; Tucker and Zhang 2011). 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 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., Schöndienst et al. 2012; Thies et al. 2014). This is particularly true for products and services financed through reward-based crowdfunding platforms such as Kickstarter. 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 (Mollick 2014). In addition to the risk of not receiving a reward at all, the quality of the reward remains unpredictable at the time the 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 (Facebook 2015). 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 (Mayzlin et al. 2014). Faking social information has thus become a preeminent threat to the credibility and trustworthiness of this type of user-generated content (Luca and Zervas 2016).

While there is a growing stream of research that is focused on uncovering non-genuine qualitative social information (e.g., Jindal et al. 2010; Hu et al. 2011; Li et al. 2011), only few studies have been devoted to identifying fake quantitative social information such as fake product rankings and ratings (e.g., Xie et al. 2012; Zhu et al. 2015). 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., Jindal et al. 2010; Li et al. 2011), 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., Xie et al. 2012; Zhu et al. 2015), 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 relatively 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.

5.2 Theoretical Background and Hypothesis Development

5.2.1 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 (Mavlanova et al. 2012). This information distortion may then lead to an adverse selection problem where consumers, when faced with a decision between two different goods, make buying decisions based on price rather than quality (Akerlof 1970).

Even though physical search costs on the internet are negligible, 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 (Krishnan and Hartline 2001). However, alternative information might only be available for established products and newness of a product or firm can thus make it harder for consumers to gather information on its true quality. 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 (Biswas and Biswas 2004). A product warranty, for example, does not change intrinsic attributes of a product but creates trust, which in turn may reduce uncertainty in buying situations (Yen 2006). Signaling theory is concerned with understanding why certain signals such as a product warranty might be reliable and could thus be relevant to the consumer in buying situations (Spence 1973).

Prior research has shown that businesses are able to signal product quality through, for example, advertising and pricing (Kirmani and Rao 2000). These signals may become even more credible to the consumers when sent by other consumers instead of businesses (Brown et al. 2007). 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 (Liu 2006) and positive customer product reviews lead to increases in book sales on Amazon (Chevalier and Mayzlin 2006). On the other hand, research on the effects of quantitative social information such as download rankings and product ratings has yielded ambiguous results. For example, Duan et al. (2009) demonstrate that, when choosing software products, consumers are strongly affected by download rankings, while product ratings only have an effect on the user's adoption of niche products and not for the adoption of popular ones. Furthermore, Hu et al. (2014) 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 by 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 with 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 (Schöndienst et al. 2012).

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., Jindal et al. 2010; Hu et al. 2011; Li et al. 2011) and few researchers also tried to detect fake quantitative social information such as fake product rankings and ratings through pattern recognition (e.g., Xie et al. 2012; Zhu et al. 2015), 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 (2016) 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. (2014) 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"* (Mayzlin et al. 2014, 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.

5.2.2 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 (Schwienbacher and Larralde 2012). It thus creates a large, relatively undefined network of project stakeholders and consequently decreases the importance of other investors such as venture capitalists.

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 (Massolution 2015). 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 (Ahlers et al. 2015). 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 (Belleflamme et al. 2014). Previous research has found these rewards to be a central reason for backers to participate in this so-called reward-based crowdfunding (Kuppuswamy and Bayus 2014). 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 (Massolution 2015).

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 (Mollick 2014). 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 (Burtch et al. 2013). We therefore argue that other evidence for the trustworthiness and quality of a campaign such as the Facebook Likes it receives becomes increasingly important for the potential backer's evaluation.

5.2.3 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 (Luca and Zervas 2016). 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 (Federal Trade Commission 2009), faking social information is still a growing trend (Sussin and Thompson 2012). Acquiring fake Facebook Likes is, for instance, possible by creating dedicated fake Facebook accounts that can then be used to *"like"* specific web pages or by turning to crowdsourcing marketplaces such as Amazon Mechanical Turk where 1,000 Facebook Likes can be acquired for as little as $15 (Arthur 2013).

Consequently, it remains challenging for providers of online services to identify social information that does not reflect genuine consumer opinions or behavior (Mayzlin et al. 2014). Popular websites such as Yelp.com use algorithms to identify and mark specific reviews as fraudulent (Jindal et al. 2010; Li et al. 2011). On Yelp, non-genuine reviews account for 16% of all reviews and tend to be particularly extreme (either favorable or unfavorable) (Luca and Zervas 2016). 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 (Xie et al. 2012; Zhu et al. 2015). 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 (Duan et al. 2008a; 2009; Cheung et al. 2014). 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 (Amblee and Bui 2011). 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 (Akerlof 1970). 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 (Spence 2002). 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 (Thies et al. 2014). Second, fake Facebook Likes are unlikely to attract any additional visitors to the campaign web page 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 web page 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 (Mollick 2014). 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 (Kirmani and Rao 2000). It has been shown that content that creates high-arousal positive emotions and is surprising, interesting, or practically useful is shared often among online users (Berger and Milkman 2012). As these are all characteristics of high-quality crowdfunding campaigns, 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 (Mollick 2014; Ahlers et al. 2015; Burtch et al. 2015). Past research has revealed that signals of quality across all crowdfunding models are effective, regardless of backer's expectations for tangible or financial returns (Mollick 2014; Burtch et al. 2015). Identified indicators of campaign quality include, for example, a campaign video, updates, the number of Facebook friends of the creator, (Mollick 2014), the description length, spelling errors, and creator experience (Wessel et al. 2015a). Consequently, campaigns on Kickstarter that provide an entertaining video and offer a detailed and vivid description of the project, offer more rewards, and engage in an active communication with the community, are inherently more shareable (Berger and Milkman 2012). 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 (Thies et al. 2014). Previous research in this context suggests 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 (Watts and Dodds 2007). 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 (Hinz et al. 2011), 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 (Kulik et al. 2008; Mayzlin et al. 2014; Branco and Villas-Boas 2015; Luca and Zervas 2016), especially if they perform poorly (Schwieren and Weichselbaumer 2010). 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 (Jong-Sung and Khagram 2005). 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 (Jong-Sung and Khagram 2005). 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.

5.3 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 (Claussen et al. 2013). 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.

5.3.1 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 (Kickstarter 2016b). 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 afterward. This usage of a temporal pattern is a common method for fraud detection (e.g., Jacob and Levitt 2003; Xie et al. 2012; Zhu et al. 2015). Jacob and Levitt (2003), 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 (Aggarwal 2013). 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 (Steuer 2013). Third, a significant drop in the additional number of additional daily Facebook Likes had to occur afterward. 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 (Aggarwal 2013). 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.

5.3.2 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 (Cameron and Trivedi 2013). We employ a fixed-effects specification (Hausman and Taylor 1981) to control for unobserved heterogeneity by estimating effects using only within project variation. Therefore, these models drop campaigns with no day-to-day variation in additional backers. Our conclusions to be discussed are generally robust to random effects models, but the performed Hausman specification test suggested that fixed-effects modeling is preferred (Hausman and Taylor 1981). The following model specification therefore results for our baseline regression:

$$y_{it} = \alpha_i + \beta x_{it} + \gamma z_i \tag{1-1}$$

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 (Allison and Waterman 2002). 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 (Claussen et al. 2013).

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 (Cameron and Trivedi 2005). Our model is therefore formalized as follows:

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

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 (Chen et al. 2009). One key element here is whether the campaign includes a video (Mollick 2014). 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 (Kickstarter 2016a).

Another indicator of quality is the number of updates to keep backers informed and engage frequently with the community (Agrawal et al. 2011; Kuppuswamy and Bayus 2014). Additional indicators are the creator experience (Zhang 2006), the duration of the campaign, and the number of offered rewards (Agrawal et al. 2011; Kuppuswamy and Bayus 2014). 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 (Agrawal et al. 2011; Kuppuswamy and Bayus 2014).

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:

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

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 (Chellappa et al. 2010). 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 (Hansen and

Haas 2001). We used the following Herfindahl–Hirschman index (HHI) from strategic management research as our measure:

$$\mathrm{HHI} = \sum_{i}^{N} b_{it}^{2}$$

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 (Hirschman 1964; Hansen and Haas 2001). 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:

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

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 (Jong-Sung and Khagram 2005).

5.3.3 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 2,279 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.

5.4 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 5-1. 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 in Table 5-2, 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 5-3 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 5-4).

Table 5-1 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	1,530.27	0	168,630
Backers	63.33	619.01	0	78,471
Accumulated funding	5,950.73	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)	2,724.99	3,195.79	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	5,291
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	2,977.12	8,351.24	263	168,630
Backers	529.80	2,219.94	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

5.4.1 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 5-1). 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.

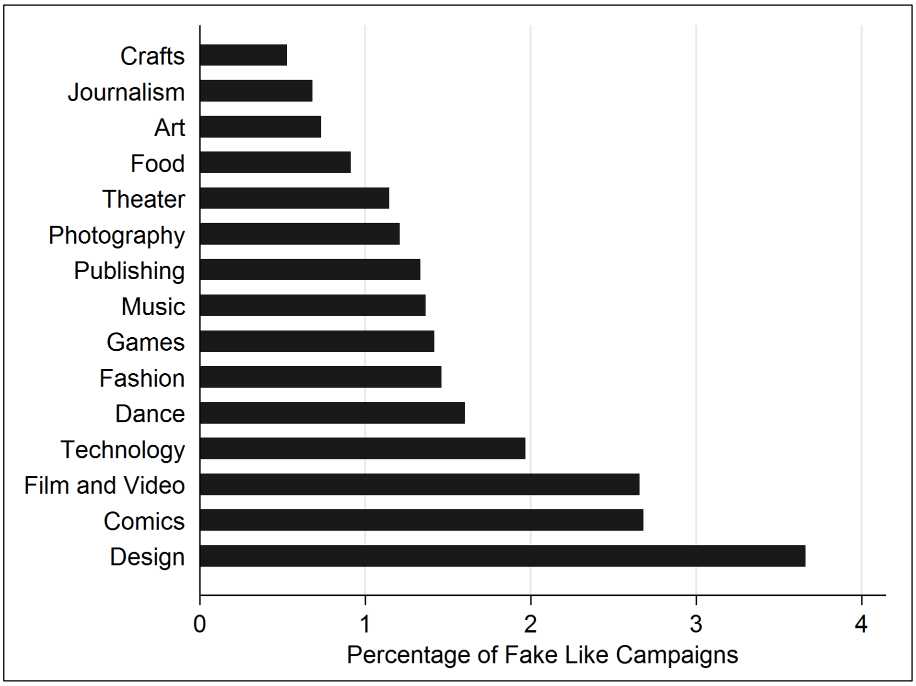

Figure 5-1 Percentage of Campaigns in the Distinct Categories on Kickstarter that Received Non-Genuine Facebook Likes During the Campaign Life Cycle

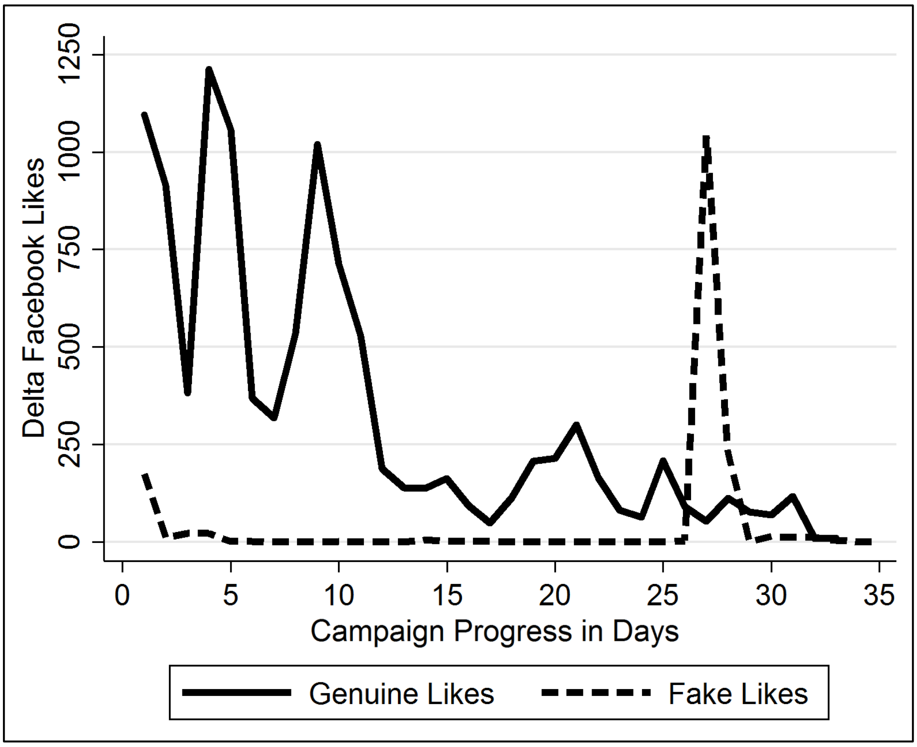

Figure 5-2 Example of Genuine and Non-Genuine Peaks in Facebook Likes

We continue by calculating the percentage of campaigns that engaged in the acquisition of fake Likes within each distinctive category as depicted in Figure 5-1. 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. Figure 5-2 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 (Figure 5-2), these peaks are not followed by a significant and sharp drop, which can therefore be used to identify fake Likes.

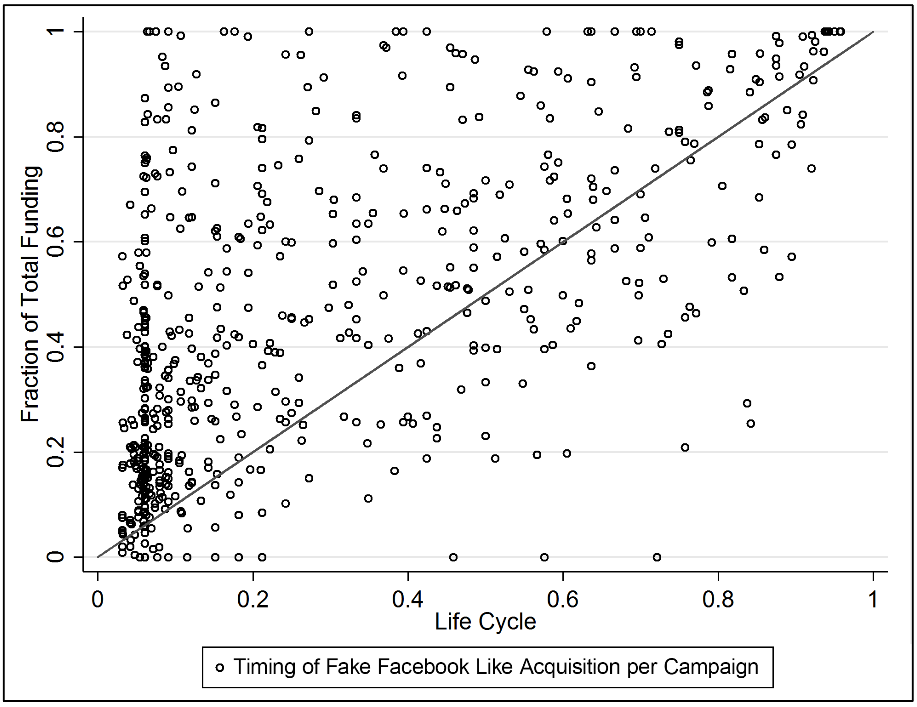

Figure 5-3 Timing of Unnatural Peaks with Respect to Funding and Life Cycle

We further use our data to plot the date of the acquisition against the accumulated funding the campaign eventually received by the end of the campaign life cycle (Figure 5-3). 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 (Hu et al. 2011). The reference line assumes a linear increase of funding during the campaign life cycle. Drawing from the representation in Figure 5-3, 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.

5.4.2 Econometric Evidence

5.4.2.1 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 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 5-2.

Table 5-2 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 Chi²	582	1,016
Campaigns	582	563
Observations	20,090	5,132

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

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. Figure 5-4 illustrates the development of additional backers per day before and after the occurrence of fake Facebook Likes.

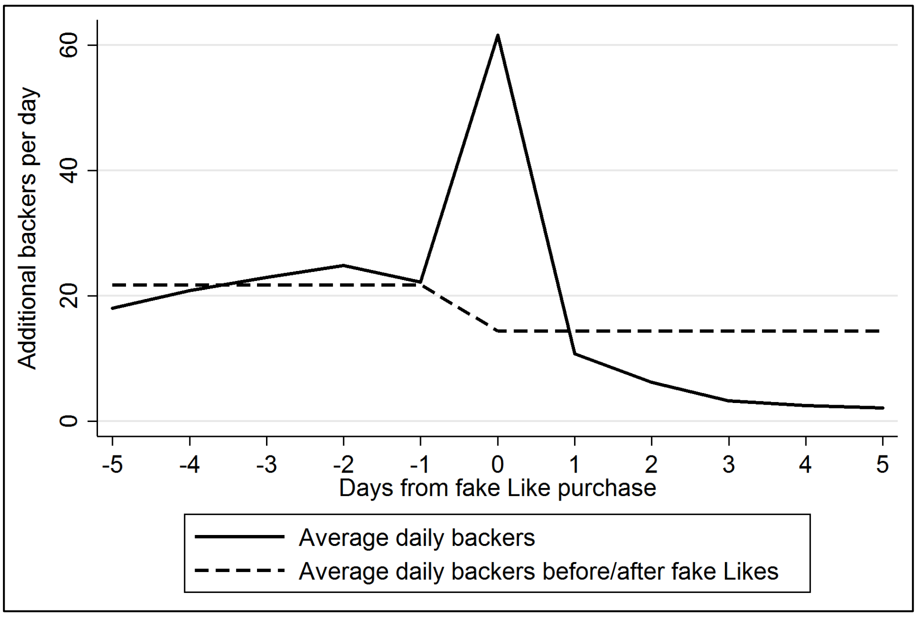

Figure 5-4 Average Daily Backers per Campaign Before and After Fake Likes

5.4.2.2 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 5-3. 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.

Table 5-3 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	5,190	2,631
Log likelihood	-2,474	-1,203
Wald Chi²	1,099	594
Pseudo R^2	0.182	0.198
Observations	36,541	17,915

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

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 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 5-3).

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 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[7].

We identified unnatural peaks in 1.6% of the campaigns on Kickstarter. Still, we showed in Figure 5-1 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 the dependent variable and the three market conditions within each category as the independent variable. The results in Table 5-4 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.

Table 5-4 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	2,645
Log likelihood	-1,306
Wald Chi²	108
Categories	15
Observations	2,848

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

5.5 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

[7] 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.

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 (Berger and Milkman 2012; Thies et al. 2014) 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 (Lee et al. 2014). 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 afterward.

5.5.1 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., Xie et al. 2012; Zhu et al. 2015).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., Chevalier and Mayzlin 2006; Duan et al. 2008b), which has also been shown for genuine Facebook Likes/Shares in the context of crowdfunding (cf., Thies et al. 2014). 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.

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., Jindal et al. 2010; Li et al. 2011), these studies have, with few exceptions (e.g., Mayzlin et al. 2014; Luca and Zervas 2016), 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 an 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.

5.5.2 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 web page 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.

5.6 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.

6 Signaling Personality Traits via Crowdfunding Campaigns

Title

Personality Matters: How Signaling Personality Traits Can Influence the Adoption and Diffusion of Crowdfunding Campaigns

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Abstract

The rapidly growing crowdfunding market allows individuals and organizations to raise funds for a diversity of projects. Potential investors, however, face uncertainties about the quality of the projects as well as the characteristics and behavioral intentions of the project creators due to a lack of publicly available and unbiased information. By analyzing 33,420 crowdfunding campaigns running on Kickstarter from January to August in 2015, we find that campaigns of project creators who are able to signal certain personality traits through their project description and video are more likely to succeed and to be shared via social media. More specifically, project creators who are able to convey openness and agreeableness are more likely to succeed with the adoption and diffusion of their campaigns compared to those signaling neuroticism. Our findings demonstrate that potential investors pay close attention to the way project creators present themselves and their projects on crowdfunding platforms. Project creators should therefore evaluate how to best communicate the favorable aspects of their project through their project description and video. Implications for future research and practice are discussed.

Keywords

Crowdfunding, personality traits, five-factor model, text analysis

6.1 Introduction

Crowdfunding allows individuals as well as organizations to raise funds for a diversity of projects through an open call on the internet. Contrary to the traditional approach of fundraising, crowdfunding is focused on collecting rather small contributions from a large number of individuals (Schwienbacher and Larralde 2012). According to an industry report, the combined crowdfunding market was worth approximately $16 billion in 2014 and is predicted to grow 100 percent in 2015 (Massolution 2015). 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 marketing activities. This development resulted in significant attention for the concept among practitioners and academics alike.

As crowdfunding platforms are two-sided markets, network effects between project creators and investors (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. Given that there is little to no publicly available information such as customer reviews for backers to evaluate prior to the investment decision, the project description and video provided by the project creator on the campaign web page become the primary source of information for backers. Therefore, the lack of credible and reliable information about the campaign and especially the project creator's characteristics and behavioral intentions poses a serious risk for the backers. The inherent information asymmetry between project creators and backers can have a dampening effect on the backers' decision to invest (Agrawal et al. 2014; Belleflamme et al. 2014). However, prior research in related fields suggests that in settings featuring high information asymmetry the ability to signal favorable aspects, such as reliability or potential success to prospective investors through the language of a proposal, can be a decisive factor in raising funds. For instance, within the context of initial public offerings, firms can reduce information asymmetries for potential investors through the wording of their prospectuses (e.g., Daily et al. 2005; Loughran and McDonald 2011; 2013). Due to the limited amount of information available prior to the investments, the rhetoric used in these brochures can send signals to the market, which can ultimately increase the potential investor's confidence or reduce the perceived risk.

Similarly, research on lending-based crowdfunding has shown that individuals signaling autonomy, competitive aggressiveness, or the willingness to take risks via their project description on the crowdfunding website are more likely to get funded compared to those signaling empathy or warmth (Herzenstein et al. 2011b; Allison et al. 2013; Moss et al. 2015). These studies show that potential investors carefully consider the manner in which language is used to describe investment opportunities. It is well-accepted in psychology and marketing literature that human language reflects the personality, thinking style, and emotional states of the authors (IBM Watson Developer Cloud 2015). Still, the importance and effects of different personalities among individuals seeking funding has been largely overlooked. However, correlations between specific personality traits and the ability of individuals to convince potential investors can be expected, as an individual's personality can be associated with different work-related attitudes and behaviors. For example, while some traits can be linked to persistence in achieving self-set work goals or organized and effective behaviors, others can be associated with low confidence and negative reactions to work-related stimuli (Costa et al. 1991; Judge and Ilies 2002; Bozionelos 2004; Devaraj et al. 2008). Personality traits can capture the mindset and behavior of an individual and prior research in areas such as entrepreneurship has shown that investors base a lot of their investment decision on the entrepreneurs themselves, by considering specific personality traits prior to investing (MacMillan et al. 1985; Sudek 2006; Cardon et al. 2009; Chen et al. 2009). However, research on the role of personality in reward-based crowdfunding remains scarce.

This paper seeks to fill this gap by investigating the language used in project descriptions and videos on Kickstarter, one of the largest reward-based crowdfunding platforms. We are using algorithms to infer the Big Five personality traits from project descriptions and video transcripts and study the effects of signaling different personality traits on the outcome of the respective campaign. Specifically, we operationalize the influence of particular personality traits and observe the effects on the adoption of the respective campaign in the marketplace and the diffusion in social media. Our research is guided by the following research questions:

RQ1: How does signaling different personality traits on Kickstarter influence the funding decision of backers and ultimately the outcome of the respective crowdfunding campaign?

RQ2: How does signaling different personality traits on Kickstarter influence the diffusion of the respective crowdfunding campaign in social media?

Our study offers important contributions to research and practice. First, it is among the first large-scale empirical studies to examine the effects of signaling specific personality traits. In doing so, we are able to show that prospective investors on crowdfunding platforms consider the personality traits reflected in the project descriptions and videos provided by the project creators for decision support. This study therefore extends prior IS research, which was mainly concerned with the effects of different personality traits of individuals on their adoption and diffusion decisions (e.g., McElroy et al. 2007; Devaraj et al. 2008; Goswami et al. 2009). Second, it adds to the growing crowdfunding literature by showing that the way in which favorable and unfavorable personality traits are expressed in project descriptions and campaign videos can have a substantial influence on the prospective backers' decision-making. Finally, and more broadly, our study builds on and enriches prior research on the Big Five personality traits (e.g., McElroy et al. 2007; Devaraj et al. 2008) and computer-aided text analysis (e.g., Short et al. 2010) to show that determining personality traits of individuals on a large scale using text analysis can open up new avenues for future research.

6.2 Theoretical Background and Prior Research

6.2.1 Personality and the Five-Factor Model

There is a growing stream of research on the effects of different personality traits in Information Systems (IS) research and in related disciplines. Researchers like McElroy et al. (2007) and Devaraj et al. (2008) encourage the IS research community to follow this endeavor as a deeper understanding of the different personality traits and their effects can not only help to conceptualize theory but also enables practitioners to better target their products and services.

Personality can be understood as a person's individual combination of traits, unique facets as well as thoughts (Barrick and Mount 1991; Devaraj et al. 2008). This dynamic set of characteristics therefore defines an individual's cognition and behavior (Maddi 1989; McElroy et al. 2007). In recent years, especially the technology acceptance and adoption community analyzed personality traits with respect to IS. For instance, Devaraj et al. (2008) examined the acceptance of collaborative technology solutions and found that personality traits influence the perceived usefulness and intention to use. Furthermore, researchers show that an individual's personality plays a critical role when receiving and evaluating information about products or services (Jahng et al. 2002; Patrakosol and Lee 2013). Different personalities value information and product presentation elements differently, which is reflected in their buying decisions (Jahng et al. 2002).

An adjacent stream of research, which contributes to the understanding of personality in our research context, is entrepreneurship. Here, controversial results on the role of personality exist. Some studies observe an entrepreneurial personality but do not find any correlation between different personalities and venture success (Stuart and Abetti 1990). Other researchers, however, find a relationship between long-term venture survival and the entrepreneur's conscientiousness (Ciavarella et al. 2004). Other studies suggest a link between a set of psychological attributes and financial performance (Begley and Boyd 1988). Findings also show that entrepreneurs have a different personality in comparison to corporate managers and small business owners (Begley and Boyd 1988; Stewart and Roth 2001; Ciavarella et al. 2004). A high need for achievement, internal locus of control, and risk-taking propensity are common personality traits among entrepreneurs (Korunka et al. 2003). Miller (2015) and Klotz and Neubaum (2016), however, emphasize the dark side of personality that is largely unexplored. Some positive aspects of personality might transform into aggressiveness, narcissism, or ruthlessness, which might hamper the growth and success of a new venture. Taken together, different personality traits of entrepreneurs have an influence on the working style and aspects of growth as well as the presentation of the ventures themselves. It is therefore not surprising that investors such as angel investors base a lot of their investment decision on the entrepreneurs themselves and consider specific personality traits prior to investing (MacMillan et al. 1985; Sudek 2006; Cardon et al. 2009; Chen et al. 2009).

In order to measure the personality of individuals, psychological trait theory has brought up several models. However, there is considerable agreement among researchers that all personality traits can be categorized in five major dimensions, often referred to as the Big Five (Goldberg 1990). The corresponding model, called the five-factor model, is the most prevalent among researchers today (Barrick et al. 2001). It has been labeled as "the model of choice for the researcher wanting to represent the domain of personality variables broadly and systematically" (Briggs 1992, p. 254).

Table 6-1 Big Five Personality Traits and the Associated Characteristics (McCrae and Costa Jr 1999; Lampe 2004)

Big Five personality trait	Characteristics
Openness	Imaginative versus down-to-earth, preference for variety versus preference for routine, independent versus confirming
Conscientiousness	Well organized versus disorganization, careful versus careless, self-disciplined versus weak-willed
Extraversion	Social versus retiring, fun-loving versus sober, affectionate versus reserved
Agreeableness	Soft-hearted versus ruthless, trusting versus suspicious, helpful versus uncooperative
Neuroticism	Worried versus calm, insecure versus secure, self-pitying versus self-satisfied

The FFM includes five primary personality traits (see Table 6-1): openness to experience (openness), conscientiousness, extraversion, agreeableness, and neuroticism (Goldberg 1990; Costa et al. 1991). Trying new and different things as well as seeking for new experiences are key traits of individuals who score high in openness (McCrae and Costa Jr 1997; Judge and Ilies 2002; McElroy et al. 2007). These curious, open-minded, and creative personalities often come up with unconventional ideas and react flexibly to challenges but are also more likely to question authority (Costa Jr and McCrae 1995). Moreover, research suggests that people who score high in openness show a positive relationship between work accomplishment and self-set goals (Judge and Ilies 2002).

Conscientiousness consists of tendencies to be intrinsically motivated, self-disciplined, and deliberate (McCrae and Costa Jr 1999; Devaraj et al. 2008). Conscientious personalities are therefore achievement oriented, ambitious, and hardworking (Barrick and Mount 1991; McElroy et al. 2007) and their plans are carried out very carefully with a focus on standards and norms (McCrae and Costa Jr 1999).

Highly social, optimistic, active, and cheerful personalities are described as being extraverted (Watson and Clark 1997; McElroy et al. 2007). They are considered to be high performers in their work life and have the ability to work very well in teams (Barrick and Mount 1991; Barrick et al. 2001). However, extraverted personalities have also been characterized as being impulsive and dominant (Watson and Clark 1997; McElroy et al. 2007).

Individuals who score high in agreeableness are likable, helpful, kind, gentle, and sympathetic (Graziano and Eisenberg 1997; Judge et al. 1999; McCrae and Costa Jr 1999). Agreeableness therefore defines a soft-hearted, trusting, and cooperative personality. It also indicates that individuals enjoy interpersonal interaction and teamwork, especially if this means to help and cooperate with others (Barrick et al. 2001).

Anxious, sad, fearful, self-conscious, and paranoid individuals usually show high values in neuroticism (Judge et al. 1999; Bozionelos 2004), while emotionally stable and well-adjusted people score low values (Devaraj et al. 2008). Neurotic personalities demonstrate a lack of psychological and emotional stability and can have difficulties in managing stress (McElroy et al. 2007). Neuroticism can therefore be associated with several negative reactions to both life and work situations and can impact perceived and actual job performance (Judge et al. 1999; Barrick et al. 2001).

Previous research shows that personality traits of individuals have an apparent and substantial influence on their behavior in a variety of contexts. However, prior IS research has almost exclusively been concerned with the personality of individuals and their varying adoption decisions. For example, researchers found that internet usage (McElroy et al. 2007) and the adoption of IT innovation depend on the individual's personality (Goswami et al. 2009). To the best of our knowledge, no prior work has investigated the effects of signaling certain personality traits through text and video on the receiver's decision-making processes.

6.2.2 Information Asymmetries in Reward-Based Crowdfunding

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

Crowdfunding also offers a variety of incentives for backers to "pledge" for a specific campaign. These incentives mainly depend on the return the backers can expect from their contributions, which range from donations to company equity (Ahlers et al. 2015). On Kickstarter, the most common and salient type of return is a so-called "reward" that often allows backers to be among the first customers to sample the product or service financed through the campaign. In this study, we focus on this so-called reward-based crowdfunding, as it is the most widespread concept of crowdfunding today.

Compared to other types of web services, reward-based crowdfunding is special as the investments made on crowdfunding platforms are especially risky as the return on investment is highly uncertain. This uncertainty results from the lack of a legal obligation to actually deliver the rewards to the backers. Also, the quality of the rewards remains unpredictable at the time the investment decision has to be made. The dynamics of crowdfunding are thus different from those in a traditional e-commerce setting between a seller and a buyer. Backers can be less certain that they will actually receive a return on their investment and have less information about the object they are investing in compared to a regular buying situation, in which the product or service already exists (Agrawal et al. 2014; Belleflamme et al. 2014).

Given that there is little to no publicly available information such as customer reviews to evaluate the investment ex-ante, backers' primary source of information is the project description and video the creator has published on the campaign web page. 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 (Burtch et al. 2013). As the project creator alone controls the flow of information towards the backer and is thus able to overstate quality or withhold information, information asymmetries may arise between prospective backers and project creators (Mavlanova et al. 2012). This results in situations, in which the project creator possesses information that the backer does not have and in which the backer is unaware of the characteristics (e.g., reliability) and behavioral intentions of the project creator. In order to help the parties overcome these information asymmetries, the backer can make inferences from credible signals sent by the project creator (Stiglitz 1990; Biswas and Biswas 2004). Signaling theory is therefore concerned with the understanding of why certain signals might be reliable and could thus be relevant to the consumer in buying situations (Spence 1973). Signals, such as a product warranty, proved only to be credible if a seller offering a low quality has higher costs acquiring them compared to a seller offering a high quality (Kirmani and Rao 2000; Connelly et al. 2011).

Prior research on lending-based and equity-based crowdfunding platforms has shown that project descriptions provided by the project creators can be credible signals for prospective backers. For instance, product creators who are able to signal autonomy, competitive aggressiveness, or the willingness to take risks through their rhetoric are more likely to receive funding (Galak et al. 2011; Ahlers et al. 2015; Allison et al. 2015; Moss et al. 2015). Though all of these studies make important contributions towards understanding how the language used in project description can help to overcome information asymmetries by signaling meaningful characteristics to prospective backers, our study extends this stream of research in three important ways. First, even though other crowdfunding models such as lending-based and equity-based crowdfunding have been considered, there are some fundamental differences in the dynamics of the different crowdfunding models and the results of previous studies might therefore not apply to our context (Beaulieu et al. 2015). Second, while other studies focused on the project descriptions, we also examine the language used in project videos. Third, ours is the first study to consider the full spectrum of personality traits reflected in the project descriptions, drawing on the comprehensive five-factor model of personality. Albeit personality traits reflected in the project descriptions and videos might not represent the exact personality of an individual project creator (e.g., several project creators or other professionals might be the authors of a single project description), both information sources are the central means for project creators to express themselves to prospective backers. Therefore, the project description and video act as the face to the customer that can be manipulated by project creators in order to influence prospective backers. Previous research found that individuals are able to perceive personality cues from different types of media, including text and voice (Nass et al. 1995; Moon and Nass 1996; Nass and Lee 2001) and are subsequently affected in their decision-making (Al-Natour et al. 2006; Hess et al. 2009).

6.3 Research Methodology

In order to examine the personality traits reflected in project descriptions and videos, we first collected data from the world's largest reward-based crowdfunding platform Kickstarter. We then sent each project description as well as video transcript to IBM's Personality Insights service via the application programming interface (API). The IBM's Personality Insights service is part of IBM's Watson computer system and is able to infer the inherent Big Five personality traits based on written text[8]. Third, we employed a probit regression model with the funding success as the binary dependent variable in order to assess the adoption of the campaigns. We then proceed to infer the diffusion of the campaign via social media, by employing a simple OLS regression with the natural logarithm of the number of Facebook shares as the dependent variable. We are therefore able to assess the influence of the different personality traits on the likelihood that prospective backers adopt a crowdfunding campaign or share it with their peers.

6.3.1 Dataset

Our dataset covers the period from January 18, 2015 to August 6, 2015 with a total of 47,526 crowdfunding campaigns on Kickstarter that started and ended within this timeframe. Following previous research, we removed campaigns with a funding goal below $100 or above $1,000,000 from the sample as these projects may have different characteristics from the majority of campaigns (Mollick 2014). We also removed campaigns with project descriptions shorter than 100 words, because they are either incomplete or represent non-serious efforts to raise funds and, more importantly, IBM's Personality Insights API requires a minimum text length of 100 words for the analysis. The final dataset consists of 33,420 campaigns, with 3,580,579 backers and approximately $324,300,000 in pledges, resulting in an average pledge of $90.50 per backer.

Besides the project description, the video, which is present on 63% of campaign web pages, is an integral part of many crowdfunding campaigns. We therefore used the Web Speech API[9] embedded in browsers such as Google Chrome to automatically transcribe the spoken words from the campaign videos into written text. This approach allowed us to transcribe almost 20,000 videos over the course of several weeks, which, due to the length requirements of IBM's Personality Insights API, resulted in 12,859 video transcripts that could be analyzed. In order to validate the performance of this approach and the accuracy of the corresponding transcripts, we exploited the fact that campaign creators are able to add subtitles to their videos and a small fraction of project creators actually uses this feature. We were therefore

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[8] https://watson-pi-demo.mybluemix.net

[9] https://dvcs.w3.org/hg/speech-api/raw-file/tip/speechapi.html

able to compare the provided subtitles of 625 campaigns with the results from the automatic transcription. For this comparison, we used Soundex, a phonetic algorithm, which is a standard feature in most database software, and achieved an average concordance rate of 79% with a median value of 88% using a cosine similarity scoring.

6.3.2 Measuring Personality Traits

An individual’s personality traits are usually measured using interviews or questionnaires. However, these approaches offer limited scalability (de Montjoye et al. 2013) and would therefore be impractical for this study considering the high number of campaigns in our dataset. An alternative, yet promising way to infer personality traits is monitoring the use of language, as personality has a so called "top-down influence" on a person's conceptualized ideas (Fast and Funder 2008, p. 334). In other words, the way in which an idea is put into words, allows the inference of a person’s personality (Fast and Funder 2008). Therefore, automatic language-analyzing techniques bear a huge potential in identifying personality traits. In the course of automated language analysis, IBM recently launched Watson’s Personality Insights services, which can be used to measure an individual’s personality based on written text. IBM’s Watson is at the forefront of a new era of cognitive computing. The artificially intelligent computer system prominently showed its capabilities in fields such as medicine or finance but also competed publicly on the television game show “Jeopardy!” and won against former winners.

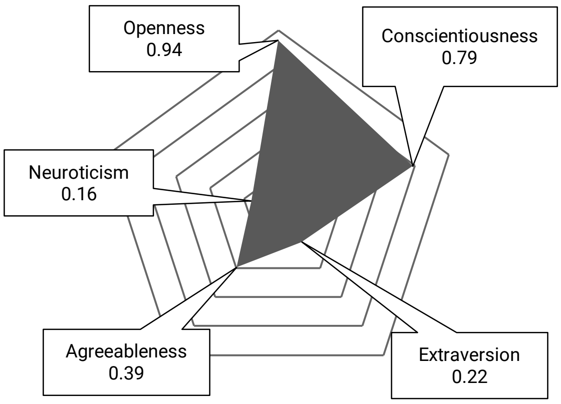
The service, which we incorporated in this study, uses linguistic analytics to infer the personality traits as well as intrinsic needs and values of individuals based on the words they are using in communications such as email, text messages, and forum posts (IBM Watson Developer Cloud 2015). To infer the Big Five personality traits, the service uses the coefficients that are reported by Yarkoni (2010), derived by comparing personality scores that were obtained from surveys to Linguistic Inquiry and Word Count (LIWC). Many prior works used the LIWC psycholinguistics dictionary to find psychologically meaningful word categories from word usage in writings (Tausczik and Pennebaker 2010; Lin and Viswanathan 2015). Once a text is sent to the Personality Insights service, it is tokenized and every token (word) is matched against the LIWC psycholinguistics dictionary in order to compute scores for every category of the dictionary. While self-reflective words about family, friends, work, feelings, and achievements as well as positive and negative emotions are used in this analysis, nouns such as names of people and places do not contribute to the personality inference (IBM Watson Developer Cloud 2015).

For the sake of demonstration, we randomly selected one project description from Kickstarter about an innovative coffee grinder[10] and show an excerpt of the input as well as the calculated output by IBM’s Personality Insights in Table 6-2. This text shows a high score in openness

[10] https://www.kickstarter.com/projects/handground/precision-coffee-grinder-better-grind-more-flavor/description

and conscientiousness, and low to medium values in neuroticism, extraversion, and agreeableness.

Table 6-2 Example Text and the Output by Personality Insights

Input (751 words)	**Output**
“The idea to make a better coffee grinder started from something we called the ‘Crowdsourced Coffee Experiment’. We were attempting to apply a Japanese principle called Kaizen to our coffee routine. It wasn’t long before we learned how important a good grinder is to making better coffee so we purchased an entry-level manual grinder. The new burr grinder was a noticeable improvement over the blade grinder, however we couldn't help but notice areas for improvement. Since Kaizen means continuous improvement we started to look for better options. Yet after searching the market and seeing the same ancient designs being repeated over and over we finally thought, we can do better. […]”	

6.3.3 Variables

As Kickstarter is applying the “all or nothing” funding model, we choose to examine funding success as the outcome variable to measure the adoption, as a high number of backers or pledges does not necessarily reflect a successful Kickstarter campaign (Rakesh et al. 2015). For instance, although a campaign with 10,000 backers and $80,000 in pledges sounds successful, with a funding goal of $500,000, the project would still fail and all invested pledges would be refunded. On the other hand, a campaign with the same outcome and a funding goal of $50,000 can clearly be regarded as successful.

As our second dependent variable, we chose the number of Facebook shares to reflect the diffusion of the campaign in social media, which has often been regarded as a crucial success factor for crowdfunding campaigns (Mollick 2014; Thies et al. 2014). As we are interested in the effects of personality traits reflected in the project descriptions and videos, we use the operationalized Big Five as our main independent variables: openness, conscientiousness, extraversion, agreeableness, and neuroticism. As mentioned before, our independent variables were gathered from the textual description of the project, as well as the automatically transcribed videos. Following prior research in crowdfunding (Burtch et al. 2013; Mollick 2014; Wessel et al. 2015b) we use a set of control variables to account for alternative explanations. Our control variables include the campaign duration, the funding goal, whether it contains a video, the category and currency, update usage, number of user comments, and the length of the text description.

6.3.4 Model

As our first dependent variable funding success is dichotomous, a probit regression that specifies the probability of an outcome as a function of one or more independent variables is applicable (Cameron and Trivedi 2005). We model the probability of a funding success depending on several basic crowdfunding variables and the personality traits. We follow Long (1997) and formalize our mode:

$$\Pr(y = 1|x) = F(x\beta)$$

where **F** is the cumulative distribution function ($\boldsymbol{\Phi}$) of the standard normal distribution for the probit model (Long 1997). The probability of witnessing a binary event given $\boldsymbol{x}$ is the cumulative density evaluated at $\boldsymbol{x\beta}$. With our dichotomous dependent variable funding success, the model can therefore be described as following.

$$\boldsymbol{Pr}(success = 1|\boldsymbol{x}) = \boldsymbol{\Phi}(\beta_0 + \beta_1 currency_i + \beta_2 \text{category}_i + \beta_3 duration_i + \beta_4 update_i + \beta_5 \ln(comments)_i + \beta_6 \ln(goal)_i + \beta_7 video_i + \beta_8 description\_length_i + \beta_9 openness_i + \beta_{10} conscientiousness_i + +\beta_{11} extraversion_i + \beta_{12} agreeableness_i + \beta_{13} neuroticism_i) + \varepsilon_i$$

where $\boldsymbol{\beta_i x_i}$ represents the independent variables and their coefficient, while ε acts as the error term.

Our second dependent variable, diffusion of the campaign, is the natural logarithm of Facebook Shares. We therefore use an OLS regression with robust standard errors (Cameron and Trivedi 2005). The formalization is, analogous to the above, as follows:

$$\ln(Facebook\ Shares)_i = \beta_0 + \beta_1 currency_i + \beta_2 \text{category}_i + \beta_3 duration_i + \beta_4 update_i + \beta_5 \ln(comments)_i + \beta_6 \ln(goal)_i + \beta_7 video_i + \beta_8 description\_length_i + \beta_9 openness_i + \beta_{10} conscientiousness_i + +\beta_{11} extraversion_i + \beta_{12} agreeableness_i + \beta_{13} neuroticism_i + \varepsilon_i$$

6.3.5 Robustness Checks

In order to check for the robustness of our research approach, we ran alternative specifications and sub samples. First, we used different dependent variables as a success measure including the natural logarithm of the funding amount using an OLS regression (Ahlers et al. 2015) and the number of campaign backers by applying a negative binominal regression (Wessel et al. 2015a). All results are in line with our original specification.

As IBM's Watson service indicates that the accuracy of their service scales with the length of the text, we also ran our original analysis with a subsample of descriptions in the 50% and 75% quantile based on the description length, which came back with the same result patterns.

6.4 Results

Descriptive statistics and the correlation matrix can be found in Table 6-3. Campaigns on Kickstarter draw an average of 91.01 backers while accumulating an average of $9,239 in our observational period. The average funding goal is $25,329. In our data, 68% of the campaigns fail to reach their funding goal, while 32% succeed in the attempt to do so. Kickstarter is publicly recommending a 30-day campaign duration, while the mean campaign duration in our data is 32.4 days with a minimum of 1 day and a maximum of 73 days (Kickstarter 2011). 63% of project creators upload a video for their campaign and project descriptions contain 561 words on average. Values of the different personality traits differ in project description or the project video. For example, the openness trait, derived from project descriptions shows on average a very high score, while the video transcribed scores show moderate average values. Still, their correlation coefficients are relatively high, ranging from 0.37 to 0.47. On the other hand, extraversion scores much higher on videos than in the textual descriptions. The relatively high correlations in Table 6-3 between the different personality traits are in line with former research and studies (e.g., Anusic et al. 2009; van der Linden et al. 2010) and are well below the threshold level to be of serious concern for the regression analysis. Table 6-4 shows the results of the econometric analysis. Models 1 and 2 are probit regressions with funding success as their dependent variable. Models 3 and 4 analyze the diffusion of a campaign through social media with an OLS regression for the number of Facebook Shares. The first column (1-1) is the baseline model, including all control variables and previously studied success factors. We then added the calculated measurements of the different personality traits in the second column of each model. We will first look at the control variables and compare our results with prior literature on reward-based crowdfunding. The increase in campaign duration is negatively associated with its adoption, as it can most likely be seen as a sign of a lack of confidence. Further, an increase of the funding goal decreases the chances of success, as it becomes more difficult to gather enough support (Mollick, 2014). On the other hand, projects with a high funding goal tend to be shared more often on social media. It is therefore crucial to find a realistic project goal, as the reciprocal effect of social media impact and backing behavior can be of reinforcing nature (Thies et al. 2014). Although the coefficient for the number of words in a project description is small, it shows a positive association between the length of a description and the adoption of a campaign, the underlying intuition being that a longer and more detailed description reduces the existing information asymmetry between creator and backers, better than a shorter description (Wessel et al. 2015a).

Table 6-3 Summary Statistics and Correlations

	Variable		Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	Success		0.32	0.46	1.000																	
(2)	Facebook Shares		303	1,983	0.474	1.000																
(3)	Duration		32.46	10.87	-0.123	0.012	1.000															
(4)	Updated		0.38	0.49	0.690	0.438	-0.071	1.000														
(5)	Comments		26.34	790	0.388	0.468	0.010	0.371	1.000													
(6)	Funding Goal (USD)		25,337	72,136	-0.249	0.209	0.221	-0.111	0.237	1.000												
(7)	Video		0.63	0.48	0.258	0.431	-0.034	0.261	0.245	0.157	1.000											
(8)	Word count		561	527	0.071	0.248	0.029	0.142	0.308	0.268	0.232	1.000										
(9)	Openness	Description text	0.81	0.21	0.046	0.083	0.012	0.062	0.086	0.094	0.102	0.175	1.000									
(10)	Conscientious.	Description text	0.73	0.22	0.105	0.144	-0.018	0.100	0.095	0.067	0.051	0.070	0.489	1.000								
(11)	Extraversion	Description text	0.42	0.32	0.029	0.096	-0.008	0.004	0.001	0.017	0.008	-0.078	-0.636	-0.306	1.000							
(12)	Agreeableness	Description text	0.52	0.34	0.043	0.091	-0.029	0.019	-0.032	-0.008	-0.019	-0.087	-0.685	-0.184	0.840	1.000						
(13)	Neuroticism	Description text	0.26	0.25	-0.115	-0.232	-0.012	-0.107	-0.186	-0.171	-0.150	-0.163	-0.403	-0.635	-0.099	0.017	1.000					
(14)	Openness	Video	0.62	0.27	0.037	0.060	0.022	0.053	0.103	0.080	.	0.122	0.395	0.267	-0.300	-0.322	-0.237	1.000				
(15)	Conscientious.	Video	0.56	0.27	0.049	0.095	0.018	0.075	0.139	0.094	.	0.092	0.214	0.367	-0.160	-0.121	-0.278	0.582	1.000			
(16)	Extraversion	Video	0.64	0.29	0.010	0.068	0.003	-0.003	-0.015	0.018	.	-0.031	-0.304	-0.171	0.465	0.409	-0.036	-0.591	-0.335	1.000		
(17)	Agreeableness	Video	0.72	0.28	0.036	0.068	-0.033	0.011	-0.055	-0.014	.	-0.073	-0.323	-0.116	0.382	0.437	0.042	-0.668	-0.212	0.754	1.000	
(18)	Neuroticism	Video	0.31	0.25	-0.018	-0.108	-0.047	-0.054	-0.168	-0.152	.	-0.119	-0.138	-0.258	-0.039	-0.002	0.432	-0.480	-0.680	-0.072	0.072	1.000

Note: *The number of observations for all variables is 33,420 (12,859 for campaigns with an eligible video). Summary statistics are presented in linear form for all variables. In the regressions the natural logarithm of Facebook Shares, Comments, and Funding Goal is used.*

Additionally, both the existence of a video and providing an update show significant impact on a campaign's chances of adoption and diffusion. Kickstarter highly recommends the creation of a project video in their frequently asked questions (FAQ). They also provide statistics, where the funding success rate of projects with a video are 50%, compared to a 30% for a campaign without a video (Kickstarter 2015a). While several studies reported that projects contain videos in 72% to 86% of all cases, having no video might be a signal for the lack of preparation (Mollick 2014; Wessel et al. 2015a). Furthermore, an active discussion around the project, measured by the number of comments, also increases the project adoption and diffusion (Mollick 2014). The coefficients in the baseline models are therefore in line with prior research.

Table 6-4 Results of the Probit and OLS Regression

Model	**(1-1)**	**(1-2)**	**(2-1)**	**(2-2)**	**(3-1)**	**(3-2)**	**(4-1)**	**(4-2)**
Personal. traits inferred from	Desc. text	Desc. text	Video	Video	Desc. text	Desc. text	Video	Video
Dep. variable	Adoption	Adoption	Adoption	Adoption	Diffusion	Diffusion	Diffusion	Diffusion
Currency (CV)	Included	Included	Included	Included	Included	Included	Included	Included
Category (CV)	Included	Included	Included	Included	Included	Included	Included	Included
Duration	-0.00918*** (-8.222)	-0.00811*** (-7.197)	-0.00837*** (-4.496)	-0.00796*** (-4.241)	-0.000741 (-0.761)	0.000347 (0.361)	-0.00124 (-0.679)	-0.000868 (-0.478)
Update	1.9*** (81.249)	1.91*** (79.893)	2.01*** (54.990)	2.01*** (54.578)	1.42*** (60.234)	1.37*** (58.771)	1.28*** (38.053)	1.25*** (37.352)
ln (Comments)	0.622*** (49.647)	0.621*** (49.120)	0.593*** (34.293)	0.598*** (34.309)	0.556*** (59.590)	0.546*** (59.303)	0.507*** (43.467)	0.507*** (43.795)
ln (Goal)	-0.454*** (-50.423)	-0.485*** (-51.791)	-0.456*** (-29.755)	-0.47*** (-30.184)	0.0898*** (12.051)	0.0721*** (9.761)	0.267*** (18.805)	0.253*** (17.968)
Video (dummy)	0.583*** (22.654)	0.53*** (20.201)			1.17*** (49.329)	1.07*** (45.084)		
Description length in words	0.000124*** (5.504)	0.000105*** (4.531)	0.0000375 (1.227)	0.0000256 (0.831)	0.000562*** (22.495)	0.000542*** (22.045)	0.000351*** (11.430)	0.000342*** (11.273)
Openness		0.314*** (3.434)		0.755*** (7.181)		0.644*** (7.939)		0.804*** (8.223)
Conscientious.		0.201* (2.345)		0.117 (1.092)		0.435*** (5.912)		0.221* (2.221)
Extraversion		-0.00644 (-0.084)		0.161 (1.512)		0.489*** (7.095)		0.505*** (4.995)
Agreeable.		0.228*** (3.393)		0.484*** (4.485)		0.323*** (5.319)		0.597*** (5.874)
Neuroticism		-0.828*** (-9.947)		0.227 (1.958)		-0.617*** (-8.366)		0.148 (1.369)
Pseudo R^2	0.574	0.586	0.557	0.562				
R^2					0.442	0.46	0.374	0.384
Observations	33,420	33,420	12,859	12,859	33,420	33,420	12,859	12,859

Note: *t statistics in parentheses. A constant is included but not reported. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

As we are interested in the differential effects of personality traits reflected in project descriptions and video transcripts, we used the personality traits derived from the description text in model 1-2 and 3-2, while model 2-2 and 4-2 include personality traits based on the video transcripts. We will therefore now discuss our focal variables with respect to their effects on adoption and diffusion and whether their value stems from the project description or the video. With regard to the adoption of a crowdfunding campaign, openness, and agreeableness appear to be the driving factors, while neuroticism in the text description has a negative and significant impact. Conscientiousness and extraversion do not play a significant role in this context (Model 1 and 2). When considering Model 3 and 4, on the other hand, conscientiousness, and extraversion gain significance and become an important driver of diffusion. Again, neuroticism decreases diffusion as well as the adoption. With regard to the effects of videos, results are similar to the text descriptions, except that neuroticism is of no particular importance here.

6.5 Discussion and Contributions

This study was motivated by the observation that, despite prior research in the context of lending-based and equity-based crowdfunding, we know little about the differential effects of different personality traits reflected in the rhetoric used by project creators on crowdfunding platforms. We are able to show a strong link between personality traits and the adoption and diffusion of Kickstarter campaigns, by demonstrating that the way in which the Big Five personality traits are expressed in the project descriptions and videos has a substantial influence on the prospective backers' decision-making. The results reveal that the personality traits openness and agreeableness are the main drivers of success, both in terms of the adoption as well as the diffusion of the campaign in social media, while conscientiousness and extraversion solely support the diffusion in social media. Neuroticism, on the other hand, is detrimental for both adoption and diffusion, when signaled through the project description and should therefore be avoided by project creators wanting to create a successful campaign.

Our findings appear to be in line with prior research on personality traits, as people with a high score in openness are known to be creative, inventive, intelligent, and curious to experience new things (McCrae and Costa Jr 1997). Prior studies have shown a positive association between openness and learning proficiency as well as the willingness to engage in learning experiences (Barrick et al. 2001). Further, Judge and Ilies (2002) found that individuals who score high in openness to experience show a positive relationship between work accomplishment and self-set goals. All these ascribed attributes do in fact reflect the very nature of crowdfunding campaigns. The second main driver, agreeableness, consists of tendencies to be helpful, gentle, trusting, and trustworthy (Graziano and Eisenberg 1997) and prioritization of work and career success (Judge et al. 1999). These attributes, again, appear to be important factors for successful campaign creators and entrepreneurs. Especially trustworthiness plays a major role in crowdfunding due to high information asymmetries between campaign creators and potential investors. As we found only little difference between personalities in written and spoken language, our results are furthermore in line with the fundamental idea behind personality traits in general psychology, being that an individual's personality can be determined by their vocabulary (Fast and Funder 2008), which is most likely not changing when writing a text or speaking in a video.

Our study extends and completes research from different areas. First, prior studies in IS and human-computer interaction (HCI) found that individuals are able to perceive personality cues from different types of media, including text and voice, which we could confirm in our study (Nass et al. 1995; Moon and Nass 1996; Nass and Lee 2001; Hess et al. 2009). Second, research on lending-based crowdfunding has shown that individuals signaling autonomy, competitive aggressiveness, or the willingness to take risks via their project description on the crowdfunding website are more likely to get funded (Herzenstein et al. 2011b; Allison et al. 2013; Moss et al. 2015). Third, the entrepreneurship literature showed that in the context of initial public offerings the rhetoric used by those seeking funding can send signals to the market, which can ultimately reduce information asymmetries (e.g., Daily et al. 2005; Loughran and McDonald 2011; 2013).

Our study makes important contributions to these streams of research and offers valuable insights for practitioners. First, to the best of our knowledge, ours is among the first large-scale empirical studies to examine the effects of signaling specific personality traits. In doing so, we are able to show that in crowdfunding the personality traits reflected in the project descriptions and videos are considered by prospective backers and used for decision support. This study therefore extends prior IS research, which was mainly concerned with the effects of different personality traits of individuals on their decision-making (e.g., McElroy et al. 2007; Devaraj et al. 2008). Second, it adds to the growing literature on crowdfunding by showing that the language used on campaign web pages can be a decisive factor for the success of crowdfunding campaigns and that specific personality traits such as openness and agreeableness can have a substantial influence on the prospective backers' decision-making when reflected in the project creators' rhetoric. Finally, and more broadly, our study builds on and enriches prior research on the Big Five personality traits and computer-aided text analysis (e.g., Short et al. 2010) to show that determining personality traits of individuals on a large scale using text analysis can open up new avenues for future research. We therefore encourage scholars to apply such means for further studies in other contexts such as e-commerce, marketing, or related fields in order to evaluate the role of personality traits in these settings.

6.5.1 Limitations, Future Research, and Conclusion

While our study provides important contributions to research and practice, we acknowledge certain limitations that have to be considered when interpreting the results and implications. In calling attention to these limitations, we hope to simultaneously suggest avenues for future research. First, although reward-based crowdfunding platforms share many characteristics with other multi-sided and e-commerce platforms, in particular, the presentation of products or services with videos and text-based descriptions, crowdfunding certainly attracts a different audience, making our findings not directly transferable to different contexts. Therefore, our findings and methodology should be validated in other settings. Second, we focused our attention on the personality traits reflected in project descriptions and videos. Obviously, other characteristics of these two information sources such as the formatting of the text or the visual component of the video can have an influence on the reader or viewer. Therefore, the analysis of these mediums is far from conclusive, but they do offer promising avenues for future research. Furthermore, we are aware of the fact that project descriptions and videos will often contain thoughts and attitudes from a group of project creators or even marketing experts rather than from a single individual. This means that the personality traits inferred from the project description and video transcript might not necessarily represent the actual personality of a specific individual. Third, due to length and methodology constraints, we focused on the Big Five personality traits that offer a broader taxonomy of an individuals' personality. However, Costa Jr and McCrae (1995) offer a more fine-grained classification of these personality traits and distinguish six facets within each of the five dimensions that should be considered in future studies for a more detailed analysis.

Finally, regarding our research methodology, some additional limitations should be considered. First, the usage of an external service such as IBM Watson or the Web Speech API should always be viewed with caution, as the underlying inferences are not fully transparent. Second, an individual's personality traits are usually measured using interviews or questionnaires (e.g., Barrick and Mount 1991; Judge and Ilies 2002; Gosling et al. 2003). Even though our data-driven approach offers several advantages (e.g., cost-effectiveness, scalability, overcoming the intention-behavior gap), it needs further confirmation in other contexts. A combination of both approaches might provide a fruitful research field and could validate our results and methodology. Third, the quality of the video transcripts could be improved, as background noise or low-quality recordings can negatively influence the transcription.

In conclusion, this study is an initial step towards understanding the effects of different personality traits reflected in project descriptions and videos in the context of reward-based crowdfunding. We hope to open up avenues for future research in this field, by demonstrating that the data-driven approach to measuring personality traits offers valuable predictive power for the assessment of the adoption in the marketplace as well as the diffusion of crowdfunding campaigns in social media.

7 Thesis Conclusion and Contributions

Crowdfunding has become an increasingly successful alternative to traditional sources of capital and is used globally to raise funds for a diversity of projects and ventures. This thesis was motivated by this growing importance of crowdfunding and the arising challenges that need to be addressed in order to avoid information-related market failure in the long term. The purpose of the thesis is to understand how and why the behaviors and actions of the distinct groups of market participants in crowdfunding can influence the level of information asymmetry on crowdfunding platforms and, ultimately, the decision-making processes of potential backers. Against this backdrop, four studies have been conducted. The main theoretical and practical contributions of these studies, and of the thesis overall, are summarized and discussed in sections 7.1 and 7.2, respectively. Though the studies are focused on crowdfunding, with a special emphasis on reward-based crowdfunding, the contributions are not strictly limited to this context, as information asymmetries are a ubiquitous phenomenon in most platform-based business models.

7.1 Theoretical Contributions

Overall, the thesis provides a deeper understanding of the dynamics on crowdfunding platforms under asymmetric information. The studies included in the thesis have been conducted in order to determine how the behaviors and actions of platform providers, project creators, and backers influence these dynamics and, eventually, the decision-making of prospective backers. Though all four studies contribute to answering the research question, they are focused on different perspectives. In the following, each perspective is therefore discussed separately.

Regarding the role of the platform provider, the findings of the first study have shown that changes in platform governance mechanisms can have considerable consequences for the overall dynamics among platform stakeholders. More specifically, by relaxing the screening or input control mechanisms, the platform provider Kickstarter removed an inherent quality signal, thereby potentially increasing the level of information asymmetry between project creators and backers. However, the results of the first study suggest that the platform users, who are faced with a larger variance in project quality after the policy change, shift their attention to alternative quality signals and focus more on the quality and characteristics of individual campaigns. These findings highlight that quality signals on platforms are fragile and vulnerable to shocks rather than static and stable over time. The study therefore provides valuable insights into the role of platform policy design, highlighting that the decision-making of platform providers can have profound effects on the dynamics among platform stakeholders. Furthermore, though input control as a critical market design mechanism has been examined in lending-based crowdfunding (Weiss et al. 2010) and other platform settings (e.g., Tiwana 2015), the study is the first to examine the effects of an extensive policy change on input control under conditions of a natural experiment. Hence, besides the contributions to the research on platform ecosystems, the study also contributes to IS control literature, emphasizing the importance of applying input control in loosely coupled ecosystems such as crowdfunding platforms.

Second, concerning the role of behaviors and actions of backers for the decision-making of future backers, study 2 and 3 provide several meaningful contributions. The second study revealed that backers consider both the prior-contribution behavior of other backers (intra-platform) as well as social buzz (cross-platform) as important quality signals in the crowdfunding context. These signals can therefore help backers to mitigate uncertainties in respect to the quality of specific crowdfunding projects. Moreover, the analysis of the dynamic relationship between prior-contribution behavior and social buzz revealed that prospective backers primarily share campaigns within their social network to demand feedback from their peers before investing themselves, rather than sharing campaigns after investing in order to encourage others to do the same. It is therefore especially interesting that social buzz (primarily on Facebook) has a strong positive effect on the decision-making of prospective backers, even though sharing via social media does not necessarily mean that the person sharing the campaign is actually financially committed to it. In contrast, non-genuine social information in the form of fake Facebook Likes does not trigger the same response from backers. The reason is that fake Facebook Likes do not disseminate through Facebook's social network, meaning that the only backers potentially affected by the increase in the number of Likes are those who see the Facebook Like button directly on the campaign web page. Therefore, even though a short-term positive effect can be induced by an artificial manipulation of social information, this effects stems from backers expediting their investment decisions based on the observed peak and the overall effect is negative. Consequently, besides advancing IS platform research, these two studies also contribute to social media research by enhancing the understanding of the effectiveness, diffusion patterns, and contextual dependencies of social buzz as a quality signal and of manipulations that might arise in this context.

Finally, the thesis also provides several contributions concerning the role of project creators in crowdfunding and how their behaviors and actions might influence the level of information asymmetry between them and backers. As the growing success of the crowdfunding concept has turned many crowdfunding platforms into noisy, crowded, and competitive markets, it is becoming increasingly difficult for project creators to stand out from the crowd and distinguish themselves from their rivals. It is therefore not surprising that project creators make use of the information advantage they have over backers and try to game the system by manipulating quality signals in order to influence the decision-making of backers in favor of their own campaign, as described in the third study. The study also uncovers product and market conditions under which the artificial manipulation of quality signals is more likely to occur. For instance, project creators who launch their campaign in categories that are focused on creative projects (e.g., arts or comics) are less likely to engage in a manipulation. This effect can possibly be attributed to the fact that campaigns in these categories tend to be shared more via social media anyway. The study also reveals that project creators are more likely to engage in unethical behavior if their campaign is published in a more competitive project category. The final study of the thesis also provides valuable contributions to IS research, by showing that personality traits project creators signal via their project description and video have an effect on prospective backers. Similar to other investors such as venture capitalists and angel investors, backers therefore, consciously or subconsciously, consider and evaluate personality traits as part of their decision-making processes (e.g., MacMillan et al. 1985; Sudek 2006; Cardon et al. 2009). The results of the study have shown that the two personality traits agreeableness and openness to experience have a positive effect on the contribution and sharing behaviors of backers, while neuroticism, when reflected in the project creators' rhetoric, has a significant negative effect. As individuals who score high on openness to experience and agreeableness have tendencies to be creative, inventive, intelligent as well as helpful, gentle, and trustworthy, it is plausible that these personality traits have the potential to mitigate uncertainties in respect to project outcomes in crowdfunding.

7.2 Practical Contributions

Beyond the theoretical contributions of the thesis, there are also a number of implications and actionable recommendations that should be considered by platform providers and complementors. Platform providers may use the findings described in the thesis in order to understand how and why certain market design mechanisms affect the information asymmetry between the market sides, thereby determining the platform's long-term prospects. The results of the first study have revealed that platform participants show a strong and immediate response if input control mechanisms, which are part of the platform's overall market design, are altered. Platform providers therefore need to be aware of any potential areas of conflict that might arise between complementors and end-users as a response to changes in the overall market design. The case of the policy change on Kickstarter has, for instance, shown that opening a platform to more complementors can have detrimental effects for the platform ecosystem. After the policy change, project creators made less effort to reduce the information asymmetry between them and potential backers and the platform also attracted a number of campaigns likely to be hoax that may be seen as a form of rebellion against the new relaxed policies (Lecher 2014). Overall, Kickstarter's decision to alter the market design unbalanced the platform ecosystem as there were, apparently, no positive cross-side network effects that would have propelled the growth of the number of backers as a response to the sharp increase in the number of new campaigns and project creators. Therefore, if platform providers should decide not to enact screening or input control mechanisms for complements submitted to the platform in order to ensure a certain level of quality, they should instead design and employ other, soft mechanisms to encourage complementors to contribute high quality complements in order to reduce information asymmetries overall. Facebook, for instance, rewards the developers of highly engaging apps with further opportunities to attract users and was able to increase the average quality of third party apps offered on the platform following this strategy (Claussen et al. 2013). Though the growth of platforms will require the providers to frequently adjust and revise the market design in order to react to the changing dynamics within the platform ecosystem, these adjustments require careful planning and testing in order to be able to predict the reactions of the platform participants.

The other studies also give insights on how to improve the market design of crowdfunding platforms in order to mitigate uncertainties for backers. The results discussed in article 2 have, for instance, shown that social buzz can be a decisive factor for a campaign's success. Though this effect strongly varies between the projects' orientations (i.e., social projects are shared significantly less via social media compared to creative projects), overall, backers seem to perceive this type of social information as an important quality signal. Platform providers can therefore internalize the positive effects of the sharing behavior of backers by offering them additional incentives to spread campaigns via social media. This could be done either directly (e.g., lower transaction fees for backers who share a campaign) or indirectly through the project creators (e.g., additional or improved rewards for sharing a campaign). Other design improvements may include more prominently displayed share buttons and notifications, highlighting the beneficial effects of sharing a campaign.

Though social buzz can be manipulated, as seen in the third study, this characteristic does not negatively affect the value of this type of social information as project creators who employ fake Facebook Likes do not gain an advantage over honest campaign creators. Nevertheless, platform providers should develop mechanisms to cope with such manipulative actions as they might hurt the overall reputation of the platform and could affect backers' trust in social information as a quality signal.

Finally, the results of the fourth study highlight the role of personality in the crowdfunding context, showing that the absence of more concrete quality signals amplifies the importance of rather subtle signals such as personality traits. Platform providers are therefore advised to develop and provide additional mechanisms that allow project creators and backers to communicate more directly and effectively. Similar to venture capitalists and angel investors who disproportionately focus on local investments in order to be able to meet entrepreneurs face-to-face, backers would benefit from a technology that allows a communication with project creators that closely resembles a face-to-face interaction. Such mechanisms could include live chats, video chats, or virtual reality features.

Though the providers of crowdfunding platforms recently started to experiment with new market design mechanisms such as insurances in order to mitigate information asymmetries (cf., Burns 2015), a certain level of uncertainty will always be involved when making transactions via crowdfunding platforms. The reason is that general project risks will remain because crowdfunding platforms, unlike venture capitalists and angel investors, will rarely be able to provide mentorship to project creators after successfully raising funds.

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