Dynamics in Platform Ecosystems

Evidence from Crowdfunding

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Abstract

Platform business models are gaining rapid traction in today's world. As of 2016, the four most valuable companies—Apple, Google, Amazon and Microsoft—have been using this business model. So do some of the most promising start-ups, including Uber and AirBnB. These providers of multi-sided platforms have a common goal, which is to match producers and consumers in order to create value through their interactions. The evolving ecosystems around a platform business are characterized by network effects among the groups of stakeholders, as each market side is influenced by the other side of the platform. A goal of the platform owner is to create and exploit as many monetization opportunities as possible. As the main revenue source, usually, is based on the interactions on or access to the platform, managing the demand and the supply side is at the core of platform management.

One example of an uprising area of business that leverages a platform business model is crowdfunding platforms. These multi-sided markets try to facilitate the interaction of individuals who seek funding for a specific project, with a crowd of people that is willing to invest in the idea. The idea behind the model has been around for a long time, but due to reduced transaction cost is now available on a global scale. As of November 2016, Kickstarter, one of the most famous players in the business of reward-based crowdfunding, has already raised 2.7 billion USD in total pledges and has funded over 114,000 projects.

This dissertation tries to shed light on the dynamics that are at work in a platform ecosystem by investigating distinct behaviors of platform participants and observing the impact on other stakeholders and the platform ecosystem as a whole. Each of the papers included in this dissertation focuses on a certain participant or dynamic of the platform ecosystem.

With the first article, the theoretical basis of asymmetric information between consumers and producers in a crowdfunding environment is established. Furthermore, it shows that the opinion expressed in the form of electronic Word-of-Mouth (eWOM) and the observable popularity information (e.g. decision-making of other participants) serve as credible quality signals, subsequently influencing consumers' decision-making. Also, popularity information and eWOM differ significantly in terms of effectiveness over time. Both factors, eWOM and popularity information, can therefore be seen as means to reduce information asymmetries in platform ecosystems.

Since the importance of popularity information and eWOM is known to producers, an incentive to manipulate these performance indicators can be deducted. We therefore suspected that producers might establish non-genuine indicators of eWOM or popularity information. Article 2 then identifies a manipulation strategy of project creators on Kickstarter, who illegally alter the number of Facebook Shares their campaign supposedly has. After identifying the fraudulent campaigns, we were able to observe the resulting effects of non-genuine social information on consumer decision-making over time, showing that a short-term gain can be achieved, whereas the total effect is indeed harmful to the campaign.

Contrary to the deliberately fake social information sent by the producers, the third article then concerns non-explicit campaign characteristics in the form of personality traits of producers. Here we were able to extract the Big Five personality traits of a project creator from the campaign description and the included video and to analyze their effectiveness for influencing potential consumers. The influence was measured by means of project adoption by the crowd and diffusion on Facebook.

Finally, article 4 investigates a governance decision made by the platform provider. Under the condition of a natural experiment, we were able to observe and analyze how a policy change by the platform owner with regard to their gatekeeping strategy can influence a platform ecosystem as a whole, as well as certain participants in particular. The policy change, made by Kickstarter in 2014, lowered the barrier for entering the platform for project creators, resulting in a shift in average quality, number of projects and platform revenue.

Implications for future research and practice are discussed in depth for each article and summarized in the final chapter.

Zusammenfassung

Plattformbasierte Geschäftsmodelle verbreiten sich immer mehr in der heutigen Geschäftswelt. 2016 bauen bereits die vier wertvollsten Firmen weltweit – Apple, Google, Amazon und Microsoft – auf diesem Geschäftsmodell auf. Gleiches gilt für äußerst erfolgversprechende Start-ups wie zum Beispiel Uber und AirBnB. Diese Anbieter von mehrseitigen Plattformen haben ein gemeinsames Ziel. Sie wollen Produzenten und Konsumenten auf einer Plattform vereinen, um durch deren Interaktion Nutzen zu generieren. Das sich daraus entwickelnde Ökosystem ist deshalb durch starke Netzeffekte zwischen den verschiedenen Teilnehmern gekennzeichnet, da jede Gruppe durch das Verhalten der anderen beeinflusst wird. Ein Ziel der Betreiber ist natürlich letztlich auch, diese Interaktion zu monetarisieren. Da die Haupteinnahmequelle üblicherweise eine Transaktionsgebühr darstellt, ist das Management der Angebots- und Nachfrageseite das Kerngeschäft eines Plattformbetreibers.

Ein Beispiel für einen sich sehr stark entwickelnden Industriezweig, der auf plattformbasierten Geschäftsmodellen fußt, sind Crowdfunding- oder sogenannte Schwarmfinanzierungs-Plattformen. Diese Betreiber mehrseitiger Märkte versuchen, die Interaktion zwischen Individuen, die auf der Suche nach finanzieller Unterstützung für ein Projekt sind, und einer Masse an Unterstützern, die bereit ist, relativ kleine Beträge zu investieren, zu ermöglichen. Die Idee hinter diesem Geschäftsmodell existiert schon sehr lange, jedoch ermöglichen es die stark gesunkenen Transaktionskosten der letzten Jahre, diese Idee auf ein globales Level zu bringen. Kickstarter, eine der bekanntesten Plattformen, konnte in weniger als acht Jahren seit ihrer Gründung bereits über 2,7 Milliarden US-Dollar für über 114.000 verschiedene Projekte einsammeln.

Motiviert durch die theoretischen Aspekte von Plattformökonomien und das aufstrebende Geschäftsmodell des Crowdfunding sollen in dieser Dissertation Dynamiken auf Plattformen beleuchtet werden. Hierfür werden bestimmte Verhaltensweisen der Teilnehmer untersucht und entsprechende Folgen und deren Einfluss auf andere Teilnehmer oder das gesamte Ökosystem analysiert. Jedes der enthaltenen Papiere fokussiert sich dabei auf einen bestimmten Teilnehmer oder einen bestimmten Mechanismus innerhalb des Plattformökosystems.

Der erste Artikel etabliert hierfür das Konzept der asymmetrischen Information zwischen Konsumenten und Produzenten im Umfeld des Crowdfunding. Der Artikel zeigt, dass Konsumenten sowohl durch die geäußerte Meinung in der Form von elektronischer Mundpropaganda als auch durch das Beobachten der Entscheidung anderer Teilnehmer sehr stark in ihrer Entscheidungsfindung beeinflusst werden. Beide Faktoren können dazu führen, dass die Informationsasymmetrien zwischen Konsumenten und Produzenten verringert werden und eine Transaktion zustande kommt.

Mit der Etablierung von Mundpropaganda als Indikator für Qualität und Entscheidungshilfe ist es naheliegend, dass Produzenten einen Anreiz haben, diesen zu manipulieren. Artikel 2 identifiziert eine eben solche Manipulationsstrategie von Erstellern von Crowdfunding-Kampagnen. Diese Strategie beinhaltet einen illegalen Zukauf von „Gefällt mir“-Angaben auf Facebook, die

auf der Webseite der Kampagne angezeigt werden. Nach der Identifizierung solcher Kampagnen konnten die resultierenden Effekte beobachtet werden. Hierbei stellte sich heraus, dass manipulierte Mundpropaganda durchaus kurzweilige positive Effekte erzeugen kann, jedoch einen negativen Gesamteffekt nach sich zieht.

Im Gegensatz zu den mutwillig gesendeten manipulierten Signalen aus Artikel 2 beschäftigt sich der dritte Artikel mit impliziten Signalen in der Form von Persönlichkeitsmerkmalen. Hierfür wurden die fünf Hauptdimensionen der Persönlichkeit (Big Five) des Kampagnenerstellers aus der Kampagnenbeschreibung und dem Kampagnenvideo extrahiert. Darauffolgend konnte der Einfluss jeder einzelnen Persönlichkeitseigenschaft auf potentielle Kunden gemessen und analysiert werden.

Der letzte Artikel dieser Dissertation beschäftigt sich dann mit dem Plattformbetreiber und einer fundamentalen strategischen Entscheidung. Unter den Bedingungen eines natürlichen Experiments konnte beobachtet werden, wie eine Lockerung der Zulassungsbeschränkung auf der Angebotsseite das gesamte Ökosystem nachhaltig beeinflusst hat.

Praktische und theoretische Implikationen werden in jedem Artikel tiefgehend diskutiert und im letzten Kapitel zusammengefasst.

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List of Abbreviations

AON	All-or-Nothing
API	Application programming interface(s)
DV	Dependent variable
eWOM	Electronic word-of-mouth
HHI	Herfindahl–Hirschman index
IRF	Impulse response function(s)
IS	Information systems
LIWC	Linguistic Inquiry and Word Count
PC	Policy change
PI	Popularity information
RQ	Research question(s)
SD	Standard deviation

1 Introduction

1.1 Motivation & Research Question

An emerging business model has gained rapid traction in the last few years. New companies such as Uber, AirBnB and Twitter were formed less than 10 years ago and have reached astonishing market valuations, while employing very few traditional resources. Paralleling their development, companies such as Google, Apple and Amazon have also experienced rapid growth and have become some of the most highly valued companies in the world. These companies appear to leverage different means to create value for themselves and their customers, as the traditional mechanics that drive business scale apparently do not apply to them (Choudary, 2015). Many of the biggest and most highly valued companies in the world, including Alibaba, Google, AirBnB, Microsoft or Visa, are what are referred to as multi-sided platforms. This means that these businesses connect members of one group with people from another group. For example, AirBnB connects people who are looking for accommodation with people who happen to offer their apartment for short-term rent. The biggest retailer worldwide, Alibaba, digitally connects buyers and sellers on their platform, without maintaining a warehouse.

These companies and business models are very different from traditional businesses that operate with a linear value chain. For instance, traditional manufacturing businesses buy raw materials, make products and sell them to their customers. The raw material of multi-sided platforms, on the other hand, is the different groups of customers that they bring together in order to facilitate their interactions (Evans et al., 2011). Multi-sided platforms therefore coordinate the demand of customer groups. Vendors of operating systems provide software that users, developers and hardware providers can use together and enable the interaction between the groups (Schmalensee and Evans, 2007). This leads to the conclusion that the purpose of the operating system vendor or the platform is shifting towards enabling efficient social and business interaction, mediated by software. In this new design, where a company is no longer the producer of value, but the enabler of interaction, two specific roles are performed by multi-sided platforms: first, they provide an open, participative infrastructure for producers and consumer to interact with each other. Second, they curate and govern the participants in order to guarantee frictionless interaction (Choudary, 2015). Despite the importance of the provider, an ecosystem evolving around a platform is also heavily dependent on the network effects among the distinct groups of stakeholders, as each participant experiences externalities (Bakos and Katsamakas, 2004; Benlian et al., 2015). This leads to a dynamic system with interdependencies between all participants. Illustrating a simple and generic platform ecosystem, Figure 1 depicts the basic components and interactions between the participants. While producers and consumer seek access to the platform in order to interact with the other side of the market, the platform provider orchestrates all participants and transactions. Deepening the understanding of the dynamics and mechanisms that are at work in these platform ecosystems is crucial for providers, producers, consumers and investors alike.

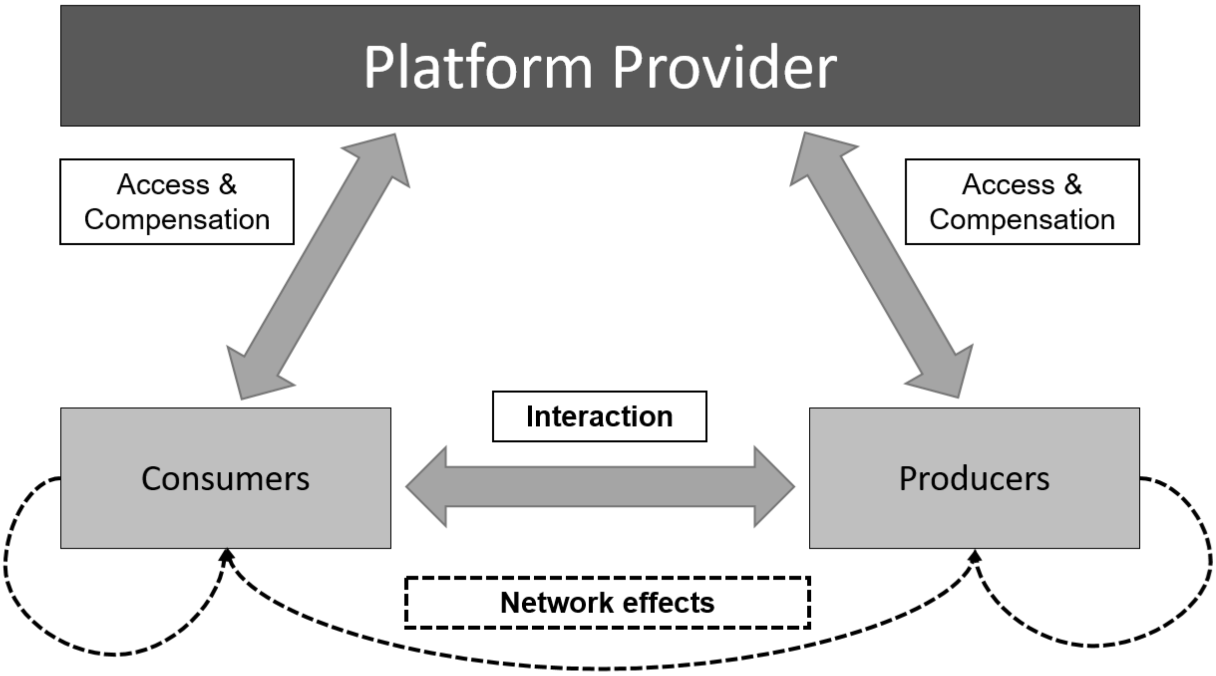


Figure 1: Platform Ecosystems

This dissertation tries to enhance current knowledge and open up new research avenues that are relevant for the academic discourse as well as applications in real-life settings. This thesis is therefore guided by the following overarching research question:

How do the actions of participants affect each other and their platform ecosystem as a whole?

In order to answer this question, the research context of crowdfunding was chosen. Crowdfunding evolved from the concept of crowdsourcing (Bayus, 2013). The neologism "crowdsourcing" is defined as the act of outsourcing a task that used to be performed internally to a large, undefined and external group of people in the form of an open call (Howe, 2008). Hence, crowdfunding allows individuals or organizations to fund a project by receiving financial contributions from a large number of individuals through an open call (Schwienbacher and Larralde, 2012). Here, the crowdfunding platform acts as an intermediary between project creators and backers of the projects. The main task of the provider is therefore to orchestrate the interaction between the participants. Given that participation in crowdfunding is mostly open to the public, this research context provides ample opportunities to observe the distinct actions of owners, consumers and producers. This data transparency and traceability over time enables researchers to investigate the consequences and dynamics for the distinct platform participants as well as the ecosystems as a whole.

1.2 Structure of the Thesis

In order to address the different aspects of the proposed research question, this thesis is subdivided into seven chapters. The motivation for the overarching research question is given in the introductory chapter. Chapter 2 then provides the theoretical foundations and establishes a common understanding of the research context. Chapter 3 to 6 consist of the four peer-reviewed and published articles that constitute the core of this cumulative dissertation. The final chapter then summarizes and recaptures the main theoretical and practical contributions.

Summaries, contributions and the articles are written from the first-person-plural point of view (i.e., *we*) in order to express that the studies were conducted with co-authors and therefore also reflect their opinions. The four articles included in this dissertation and their respective publication outlets and dates are:

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

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

Thies, F.; Wessel, M; Rudolph, J.; Benlian, A. (2016) *"Personality Matters: How Signaling Personality Traits Can Influence the Adoption and Diffusion of Crowdfunding Campaigns"*
In: 24th European Conference on Information Systems (ECIS), Istanbul, Turkey. **VHB: B**

Wessel, Michael and Thies, Ferdinand and Benlian, Alexander (2015) *"The Effects of Relinquishing Control in Platform Ecosystems: Implications from a Policy Change on Kickstarter"*
In: International Conference on Information Systems (ICIS), Fort Worth, USA. **VHB: A**

Each article addresses a different aspect of the general research question and has undergone a slight editorial revision in order to provide a consistent layout throughout this dissertation. An overview of how each article aligns with the general platform framework is given in Figure 2.

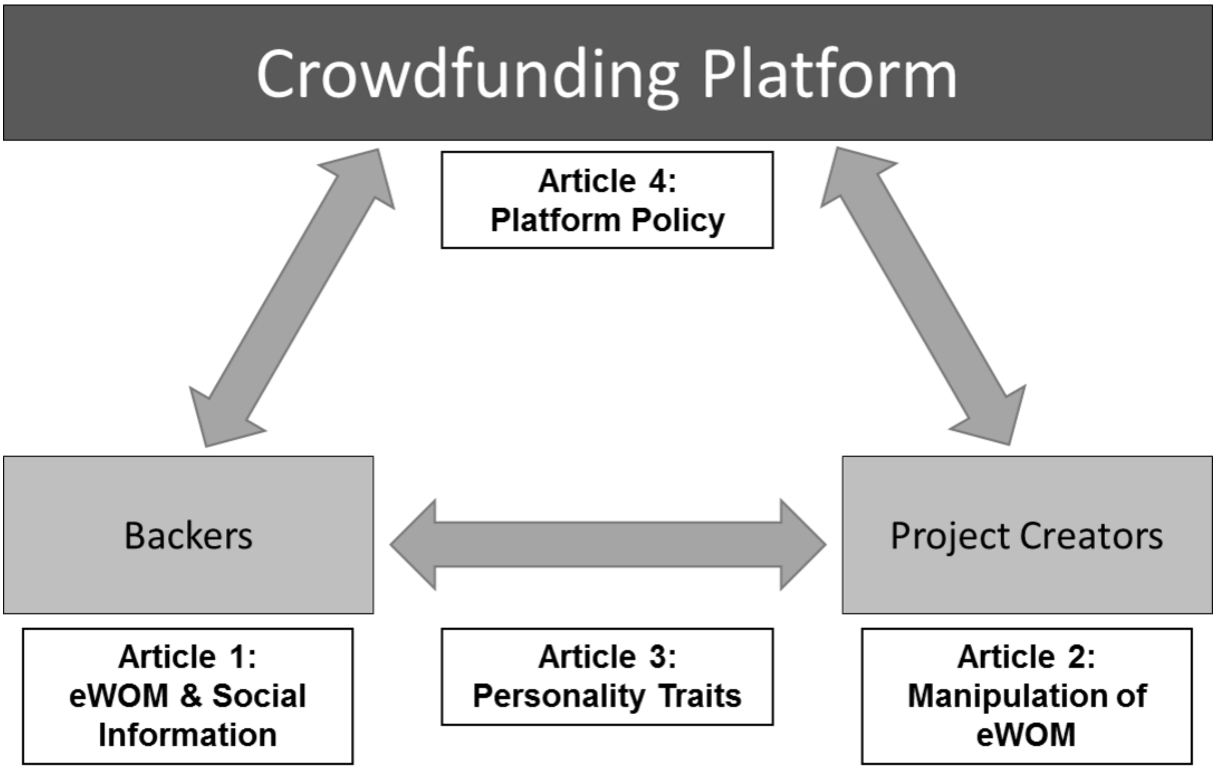


Figure 2: Thesis Overview

In the following, each article is summarized shortly and the main findings in relation to the overarching research question are presented.

Article 1 (chapter 3) establishes the importance of asymmetric information between project backers and creators. Furthermore, it provides evidence of how and to what extent popularity information and electronic Word-of-Mouth (eWOM) influence the decision-making of project backers under uncertainty. The results are based on a panel vector autoregressive analysis with a dataset consisting of approximately 23.000 crowdfunding campaigns that ran on the platform Indiegogo between November 2013 and June 2014. The study contributes to the extant literature by providing a better understanding of the dynamic effects of opinion-based and action-based social interactions, showing that social interactions are perceived as quality indicators on crowdfunding platforms. The first paper therefore addresses how the actions and opinions of consumers influence the decision-making of other potential consumers.

Building on the importance of eWOM and the growing success of social media, a strong presence of social information, such as customer product reviews and product ratings in electronic markets, incentivizes producers to game the system by creating fake data. Article 2 (chapter 4) identifies such a manipulation strategy of producers and the resulting effects of fake social information on consumer decision-making. Analyzing over 80,000 campaigns that ran on Kickstarter and Indiegogo from November 15th 2013 to August 18th 2014 with over 1.85 million data points, we were able to show that a positive and significant short-term effect can be induced by a manipulation of social information. However, the total effect of a manipulation strategy is harmful for the funding outcome. This shows that consumers are aware of the strategies and abandon the respective projects. With regard to the initial research question, this chapter provides evidence of how the actions of producers prevent consumers from adopting a project.

With the aforementioned information asymmetries in mind, potential investors face uncertainties not only concerning the quality of the projects but also the characteristics and behavioral intentions of the project creators. Article 3 (chapter 5) therefore looks into the influence of a creator's personality traits that are signaled via the respective campaign description and video on the decision-making of consumers. Here our final dataset consisted of 33,420 campaigns, with over 3.5 million backers and approximately $324,300,000 in pledges. We were then able to demonstrate that the personality traits openness and agreeableness conveyed by the description and the video are favorable to the funding success of a project. Showing signs of neuroticism, on the other hand, significantly reduces the funding probability. Our findings demonstrate that potential investors pay close attention to the way project creators present themselves and their projects on crowdfunding platforms. Concerning the research question, this paper again focuses on the actions of producers and shows how their characteristics play an important role in the decision-making process of consumers.

So far, the articles have focused on the actions, behaviors and characteristics of producers and consumers in a platform ecosystem. However, platform providers naturally preside over the platform and their actions are highly influential. Hence, article 4 (chapter 6) examines a governance decision of the platform provider and how it affected the ecosystem as a whole and participants in particular. The decision in question was a policy change regarding the gatekeeping process of the platform. After the policy change, it was much easier to access the platform as a project creator. By analyzing over 67,000 Kickstarter campaigns under the conditions of a natural experiment over a one-year period, we were able to show that loosening the control mechanisms led to a general decline in project quality and funding. On the other hand, platform indicators suggest that the policy change has indeed increased platform revenue, as the larger number of campaigns compensated for the lower average revenue per campaign. Producers are therefore confronted with a higher level of competition, while consumers face greater uncertainties about campaign quality, but also more offerings to choose from. Concluding the thesis, the fourth article addresses the final aspect of the initial research question by demonstrating how the platform provider's actions can fundamentally alter the dynamics of a platform ecosystem.

In addition to the articles included in the thesis, the following articles (Table 1) were also published or are still under review during my time as a PhD candidate. They are, however, not part of this dissertation:

Table 1: Additional Articles

Authors	**Title**	**Outlet**	**VHB**	**Publication Status**
Wessel, M.; Thies, F.; Benlian, A.	*"The Implications of Increasing Platform Openness: Exploratory Evidence from a Policy Change on Kickstarter"*	Journal of Information Technology (JIT)	A	2nd Review Round
Thies, F.; Wessel, M.; Benlian, A.	*"The Implications of Relaxing Input Control for Entrepreneurial Crowdfunding Initiatives — Evidence from a Natural Experiment on Kickstarter"*	Information Systems Journal (ISJ)	A	2nd Review Round
Wessel, M.; Thies, F.; Benlian, A.	*"The Emergence and Effects of Fake Social Information: Evidence from Crowdfunding"*	Decision Support Systems (90), pp. 75-85	B	Published 2016
Wessel, M.; Thies, F.	*"The Effects of Personalization on Purchase Intentions for Online News: An Experimental Study of Different Personalization Increments."*	23rd European Conference on Information Systems (ECIS)	B	Published 2015; **Best Paper Award: Full Research Paper**
Stadler, M.; Thies, F.; Wessel, M.; Benlian, A.	*"Erfolg von Crowdfunding-Kampagnen frühzeitig erkennen: Erfolgsprädiktoren auf Kickstarter und Indiegogo"*	Internationale Tagung Wirtschaftsinformatik (WI)	C	Published 2015
Thies, F.; Wessel, M.; Benlian, A.	*"Understanding the Dynamic Interplay of Social Buzz and Contribution Behavior within and between Online Platforms – Evidence from Crowdfunding"*	International Conference on Information Systems (ICIS)	A	Published 2014; **Best Paper Runner Up: Full Research Paper**
Thies, F.; Wessel, M.	*"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 (ECIS)	B	Published 2014

2 Theoretical Background

The theoretical foundation of this dissertation consists of three main aspects that will briefly be presented in the following sections and put into perspective with the research context. First, an introduction to platform economics is given, detailing the dynamics and mechanism of platform-based business and their impact on industries as well as consumers. Second, platform governance mechanisms that can be used by the owner are introduced, which can be summarized under the term of platform control. Third, information asymmetries and quality signals are presented in the light of interactions in platform ecosystems. Finally, the aforementioned theoretical foundations are applied in the research context of crowdfunding platforms.

2.1 Platform Economics

Platforms have become a ubiquitous phenomenon in today's world, and the business model associated with them has turned whole industries upside down.

Two-sided platforms were first identified by Jean Charles Rochet and Jean Tirole in 2001. Their subsequent pioneering work attracted scholars and practitioners alike, leading to a significant theoretical and empirical literature.

While a platform is 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), in the context of this thesis the established view is that platforms are defined as all "products and services that bring together groups of users in two-sided networks" (Eisenmann et al., 2006, p. 2). Evans and Schmalensee (2016) add to the definition by calling multi-sided platforms *"matchmakers that connect one group of customers with another group of customers."*

An ecosystem evolving around a platform can therefore be characterized by network effects among the distinct groups of stakeholders, as each side derives positive externalities from the participation of the other side (Bakos and Katsamakas, 2004; Benlian et al., 2015). In this regard, the success of a platform ecosystem strongly correlates with the availability of compelling products that attract a sufficiently high number of interested consumers. However, complementors will only be willing to contribute products if the platform provides sufficient incentives to do so, such as a reasonable commission on profit and a sufficient number of potential customers (Rochet and Tirole, 2003). Creating favorable conditions for these network effects to emerge is thus at the core of platform management.

For the sake of clarity, some intuitions of the economics of two-sided platforms shall be explained with the help of an example: a heterosexual, single-oriented club. A club or a bar provides men and women with the opportunity of meeting and dating by giving them a common platform for interaction. The owner of the club needs to get the two groups of customers on board in order to provide the promised possibility to interact and create value in the process. However, the balance of men and women matters a great deal to each party. A bar with very few women will not attract men and vice versa. Here, pricing is a common mechanism to balance the number of men and women. A club might offer lower entrance fees or free drinks if women are in short supply. More popular clubs with queues outside can adjust their door policy and hand-pick the participants to get the balance right. Here, typically women are picked out disproportionally (Evans et al., 2011).

2.2 Information Asymmetries & Quality Signals

Even though the goal of the platform provider is to create favorable conditions for the exchange of services and goods, the quality is often difficult to ascertain. Digital platforms lack physical contact, which prevents consumers from touching, smelling or tasting a product in order to evaluate its quality (Mavlanova et al., 2012). This results in a situation where a consumer can only learn about the true quality after the delivery of the service or good. Therefore, only the producer knows about the quality of the product beforehand. This difference in information allocation between producers and consumers is known as information asymmetry and can lead to an adverse selection problem where consumers make buying decisions based on limited information, such as price (Akerlof, 1970). In platform ecosystems or online purchases, information asymmetry can be intensified, as the producer alone controls the flow of information towards the consumer and is thus able to overstate quality or withhold information (Mavlanova et al., 2012).

Even though physical search costs on the internet are extremely low, search costs may still arise due to the difficulty of evaluating service quality. Therefore, other forms of information sources might gain more attention. This phenomenon was, for example, confirmed for brand equity in services (Krishnan and Hartline, 2001).

However, alternative sources of information might not always be available. Whereas established products are often extensively reviewed and tested, innovative and new products or firms make it harder for potential customers to gather information on the true quality. Therefore, the consumer can draw inferences about the true quality from credible signals sent by the complementor (Biswas and Biswas, 2004). Extensive research has been conducted on what is collectively referred to as signaling theory, to understand which signals might be reliable and could thus be relevant for the consumer in buying situations (Spence, 2002). Prior research has shown that businesses are able to signal product quality through, for example, advertising, pricing or product warranties, even though those aspects are detached from product quality itself (Kirmani and Rao, 2000; Yen, 2006). However, these quality signals might become even more credible to customers when sent by other customers instead of businesses. Platforms usually allow or even encourage their consumers to exchange opinions and recommendations on a large scale through social information, such as online customer product ratings and voting. This form of scaling quality is often termed social curation and—from a provider's perspective—provides a very efficient way of controlling product quality (Choudary, 2015).

Going back to the nightclub example, signaling quality is crucial before interactions take place. Here, both groups of customers try to present themselves as favorable as possible. These efforts might include dressing up or excessive spending. One might even refer to signaling as a way of showing off. Whether these signals constitute true quality remains to be seen.

2.3 Platform Governance

Operators of platforms face the enduring challenge of aligning their own objectives with those of the main stakeholders within the platform ecosystem. Platform governance, which can generally be defined as *"who makes what decisions about a platform"* (Tiwana et al., 2010, p. 679), plays a crucial role for platform owners. The need to involve and engage platform participants requires them to make deliberate choices about decision rights, ownership and control. Platform governance is closely aligned with controlling the stakeholders of a platform ecosystem. Classical literature circumscribes control as mechanisms that are used by controllers in the attempt to influence controlees so that they act and behave in accordance with the controller's objectives (Kirsch, 1997; Ouchi, 1979). Here, two main categories of control have been distinguished, namely formal and informal control (e.g., Kirsch, 1996), which are further subdivided into different modes. In the category of formal control, two distinct approaches have been identified, namely output (also referred to as outcome) and process (also referred to as behavior) control (e.g., Eisenhardt, 1985; Ouchi, 1979).

Output control refers to a set of rules where the controlee is required to reach a certain goal or objective given by the controller in order to be rewarded. Process control, on the other hand, obligates the controlee to adhere to specified procedures and routines during the process. In contrast, informal control modes do not require specific incentives to align the goals of controller and controlee, as norms and values are shared among both parties (Kirsch et al., 2002).

Within informal control, the literature distinguishes self- and clan control (e.g., Kirsch, 1996; Ouchi, 1979). Self-control exists when controlees define and monitor their own goal achievement and reward or punish themselves accordingly. Clan control is closely related to self-control with the distinction that a group of controlees, rather than an individual controlee, embrace shared values and commit to achieving common goals (Kirsch et al., 2002).

Originating from organizational theory, the concept of control has drawn considerable attention among scholars of information systems (e.g., Kirsch et al., 2002; Kirsch, 1997; Tiwana and Keil, 2009). However, it was only applied in the context of digital platforms quite recently (e.g., Ghazawneh and Henfridsson, 2013; Wareham et al., 2014; Goldbach et al., 2014). This is not surprising, as the aforementioned transformation of business models towards platforms is still ongoing. Still, the relevance of the formal and informal control mechanisms mentioned is decreasing in platform contexts due to redundancy and costliness (Tiwana, 2015).

More precisely, process control is often obsolete, due to the fact that platform owners are ultimately only interested in the final complement (e.g., mobile apps, crowdfunding projects or a ride on Uber).

Costs that have to be borne by the complementors to deliver the product are of very little concern to the platform provider, as their relationship is not a classical principal-agent relationship, where a complementor is hired by a provider. Also, in order to establish an effective clan control mechanism, a relatively stable ecosystem with frequent interactions is required. Following this line of argument, it can be concluded that formal and informal control mechanisms are *"less viable in loosely coupled organizational structures"* (Tiwana, 2015, p. 4).

In an ecosystem with high fluctuations in terms of complementors, providers therefore focus their efforts towards input control mechanisms. Input control is a formal control mechanism that can be defined by the degree to which platform providers use a predefined set of rules and guidelines to decide whether a participant should be allowed into the platform (Cardinal et al., 2004; Tiwana et al., 2010).

Once again, referring back to the example of the nightclub above, this mechanism is fairly well mirrored in the door policy of an establishment, where a gatekeeper decides who may enter the club and who may not, based on a set of rules, such as the attire or looks.

In a platform setting the purpose of input control is therefore to ensure that complementors abide by the rules and standards set by the provider in order to guarantee that the values and goals of the participants are closely aligned (Maurer and Tiwana, 2012). However, too much alignment might backfire. First, especially in nascent markets where consumer preferences are not yet settled, forcing producers to comply with established rules could hinder innovation (Claussen et al., 2013). Second, input control poses upfront costs for the screening process that could become unbearable for the provider if the number of complementors rises disproportionally due to triggered network effects and exponential growth. Still, research has shown that the mere perception of an established input control mechanism will induce complementors to pay more attention to the rules (Aghion and Tirole, 1997). This implies that *"greater use of input control can by itself reduce its need"* (Tiwana, 2015, p. 6).

This arising trade-off between retaining and relinquishing control has received increasing attention among scholars and practitioners alike, where the apparent differences in input control exercised by the platform owner are often coined as the degree of platform openness (e.g., Boudreau, 2010; Cusumano, 2010; Benlian et al., 2015; Ondrus et al., 2015; Wareham et al., 2014).

2.4 Conceptual Foundations of Crowdfunding

Crowdfunding builds on the broader concept of crowdsourcing (Bayus, 2013) as it allows individuals or organizations to fund a project by receiving small financial contributions from a large number of individuals through an open call—mostly on the Internet (Schwienbacher and

Larralde, 2012). This is contrary to the traditional approach of funding where large contributions from a small number of investors are received.

The reasons project creators opt for crowdfunding instead of traditional funding methods are not limited to financial aspects. First, the success of the campaign also validates that there is a market for the respective product or service. Second, the campaigns themselves can also serve as a marketing tool to draw attention to the proposed product idea (Burtch et al., 2013; Mollick, 2014).

This thesis focuses on reward-based crowdfunding. Unlike with equity-based and lending-based crowdfunding, where backers can generate revenue through private equity in the respective company or through interest on the amount invested, no financial benefits are offered in this case. Instead, backers can expect to receive a tangible benefit from their investment (e.g., early and discounted purchase of the product or service). These rewards, however, have a high level of uncertainty, as backers cannot judge the quality when making their investment decision. Additionally, further conditions must be met before rewards can be delivered to the backers of a campaign. One fundamental condition is that the campaign is successful, meaning that enough funds are raised within the pre-arranged campaign runtime to bring the project to life. Depending on the different crowdfunding platforms, project creators receive the pledged funds regardless of whether their funding goal is reached (e.g. Indiegogo), or the funds are only paid out if the funding goal is reached. The latter is commonly called the "All-or-Nothing" (AoN) funding model and is prominently used by Kickstarter. Also, an investment in a crowdfunding campaign cannot be equated to a purchase, since there is usually no legal obligation for the creator to produce and deliver the reward (Mollick, 2014). In sum, backers can be less certain that they will receive any return on their investment and have very little information about the promised reward compared to a regular buying situation, in which a product can be inspected thoroughly. Still, previous research has shown that rewards are a central reason for backers to participate in reward-based crowdfunding (Kuppuswamy and Bayus, 2014). The resulting information asymmetries need to be mitigated by the project creator in order to convince potential backers of the project quality. The methods to do so usually consist of the textual campaign description the creator publishes on the platform and often includes a short video, showing the creator, possibly a prototype, the finished product or other important aspects of the campaign. Due to the possibility for consumers to exchange opinions and recommendations on a large scale, social curation is expected to play an important role in ensuring project quality and reducing information asymmetries (Choudary, 2015).

For the purpose of illustrating the information a potential backer has before deciding to back a campaign, a typical campaign homepage is shown in Figure 3. The page is dominated by the video (1) in the center accompanied by the textual description (2) of the project below. Other aforementioned features such as a quantitative measure of eWOM (3), for example in the form of Facebook Shares or on-site comments, are placed around the center. Popularity information (4), including the number of backers and the funding volume, is also prominently shown on the upper right side. Furthermore, short information on the creator (5) is given on the right, and the promised rewards (6) are described on the bottom right, including the required pledge for each reward.

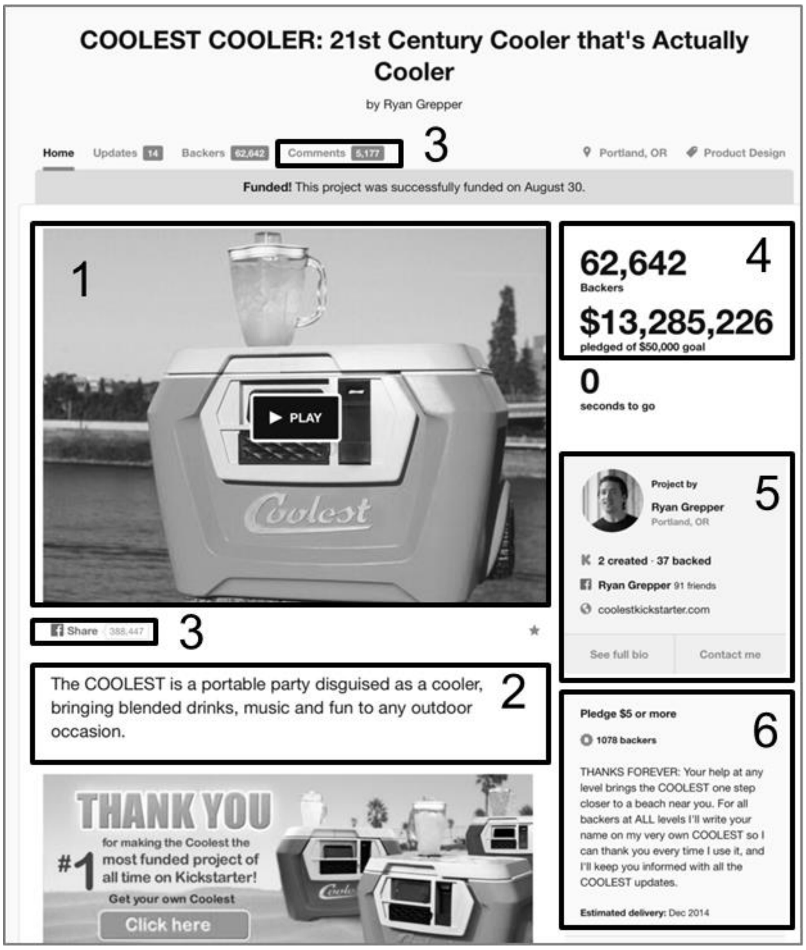


Figure 3: Campaign Page on Kickstarter

As creators usually do not launch multiple projects, a crowdfunding campaign is most often a one-off process and the platform can be regarded as a loosely coupled organizational structure (Tiwana, 2014), where input control mechanisms are highly relevant. This means that the gate-keeping process and the decision who may enter the platform as a creator should be of great importance. In sum, crowdfunding provides extremely fruitful grounds for investigating the dynamics of platform ecosystems under the lenses of information asymmetries, social interactions and platform governance. In the context of crowdfunding and this dissertation, the terms project creator, producer and complementor are used interchangeably. The same applies to backers, consumers and funders.

With the basic theoretical background established, the following chapters 3 to 6 consist of the aforementioned articles. Each chapter is concerned with a different aspect of the dynamics of a platform ecosystem.

3 Social Interaction on Platforms

Title:	Effects of Social Interaction Dynamics on Platforms (2016)
Authors:	Thies, Ferdinand
	Wessel, Michael
	Benlian, Alexander
Published in:	Journal of Management Information Systems, 33 (3)

Abstract

Despite the increasing relevance of online social interactions on platforms, there is still little research on the temporal dynamics between electronic word-of-mouth (a form of opinion-based social interaction), popularity information (a form of action-based social interaction), and consumer decision-making. Drawing on a panel dataset of more than 23,300 crowdfunding campaigns from Indiegogo, we investigate the dynamic effects of these social interactions on consumers' funding decisions using the panel vector autoregressive methodology. Our analysis shows that both electronic word-of-mouth and popularity information are critical influencing mechanisms in crowdfunding. However, our overarching finding is that electronic word-of-mouth surrounding crowdfunding campaigns on Indiegogo or Facebook has a significant yet substantially weaker predictive power than popularity information. We also find that whereas popularity information has a more immediate effect on consumers' funding behavior, its effectiveness decays rather quickly, while the impact of electronic word-of-mouth recedes more slowly. This study contributes to the extant literature by (1) providing a more nuanced understanding of the dynamic effects of opinion-based and action-based social interactions, (2) unraveling both within-platform and cross-platform dynamics, and (3) showing that social interactions are perceived as quality indicators on crowdfunding platforms that help consumers reduce risks associated with their investment decisions. The key practical implication is that a more nuanced understanding of the dynamic impact of social interactions within and across platforms can help platform providers and complementors to stimulate contribution behavior and increase platform prosperity overall.

Keywords: *electronic word-of-mouth, popularity information, informational cascades, reward-based crowdfunding, panel vector autoregression*

3.1 Introduction

Consumers tend to consider other people's opinions and actions when they make buying decisions. For instance, a person might choose to visit a restaurant based on a friend's recommendation or its observable popularity (Becker, 1991). Given that online transactions restrict consumers' ability to assess a product's quality due to the lack of direct interaction with product and seller, these social interactions play a particularly critical role in electronic markets and have become a vital quality indication for consumers to use for decision support (Dellarocas, 2003; Godes et al., 2005).

Social interactions have been generally defined as "*actions [...] taken by an individual not actively engaged in selling the product or service and that impact others' expected utility for that product or service*" (Godes et al., 2005, p. 416-417). Previous research distinguished between two distinct types of social interactions that have been shown to be particularly relevant in an online context, namely opinion-based or preference-based and action-based or behavior-based social interactions (e.g., (Chen et al., 2011; Cheung et al., 2014; Tucker and Zhang, 2011)). The former type is often referred to as electronic word-of-mouth (eWOM) communication in an online context and can be described as a statement by potential, actual, or former customers about a product or company (Hennig-Thurau et al., 2004). The latter type, often facilitated through popularity information (PI), becomes relevant in situations in which individuals who face identical decisions under uncertainty can observe the actions of other consumers (e.g., in the form of aggregated statistics displaying the number of downloads or purchases of a product) who faced the same decisions earlier on, but not the motivation behind their actions (Bikhchandani et al., 1992; Bikhchandani et al., 1998). These situations can lead 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 instead of taking a decision based on their own private information (Bikhchandani et al., 1992; Tucker and Zhang, 2011; Bikhchandani et al., 1998; Duan et al., 2009).

The Internet offers consumers various opportunities to engage in online social interactions with their peers and other consumers via, for example, online review platforms, social networking websites, blogs, and online forums. These interactions help them to overcome the information asymmetry for products and services whose quality is difficult to ascertain before purchase. E-commerce vendors have also recognized the critical role of social interactions among consumers to influence their purchasing decisions and platforms provide informational cues in order to facilitate these interactions. Amazon.com, for example, facilitates the dissemination of eWOM by encouraging consumers to publish product reviews, but also depicts popularity information by showing sales rankings and by highlighting top selling products in each product category.

Motivated by the practical relevance of online social interactions, researchers dedicated a number of important studies to the phenomenon. For example, Luo and Zhang (2013) have shown that consumer buzz and firm value not only affect one another over time, but that consumer buzz also has autoregressive carry-over effects so that past buzz influences current buzz, highlighting the self-reinforcing nature of opinion-based social interactions. Duan et al. (2009) empirically demonstrated the existence of complex informational cascades between other users' software download behavior (as indicated by popularity information) and subsequent software downloads, revealing dynamic co-movements between user actions on platforms.

While previous research examined the effects of the two types of online social interactions separately in various settings (e.g., (Duan et al., 2008; Duan et al., 2009; Forman et al., 2008; Liu, 2006)), only a few studies, such as Chen et al. (2011) and Cheung et al. (2014), considered both types simultaneously and examined their relative impact on consumer decision-making. However, there is still little understanding of how dynamic these effects are and how quickly or slowly they unfold and evolve. Such an assessment is crucial in order to understand at which point in time online social interactions have the biggest effect on consumer decision-making, given the fast-paced speed of decisions in the online world. Thus, there is a clear need to examine how these mechanisms weigh up in their predictive ability as well as how they differentially affect one another over time. This study attempts to fill this research gap, guided by the following research question:

> ***RQ:*** *What are the effects of opinion-based and action-based online social interactions on consumer decision-making and how do these effects build up and decay over time?*

To answer our research question, we focus on crowdfunding, a context in which social interactions play a particularly important role. Crowdfunding allows individuals or organizations to raise funds for diverse projects by receiving small financial contributions from a large number of individual investors (Mollick, 2014). As investments in crowdfunding campaigns can be considered risky for the investors due to limited information about the projects and uncertain outcomes, it becomes optimal for investors to infer the quality of campaigns from the opinions and actions of other consumers.

We collected daily project-level data from Indiegogo, one of the largest reward-based crowdfunding platforms. Since its launch in 2008, more than 400,000 campaigns have run on Indiegogo and millions of dollars have been distributed to campaign creators (Mearian, 2016). We complemented this dataset with corresponding eWOM data gathered from Facebook and Indiegogo itself. Using daily data on more than 23,300 crowdfunding campaigns that ran between November 2013 and June 2014, we analyze the dynamic effects of eWOM and PI on subsequent campaign funding decisions using the panel vector autoregressive (PVAR) methodology.

Our findings provide noteworthy contributions to theory and practice. First, we contribute to the software platform and social media literature by providing a more nuanced understanding of eWOM's and PI's dynamic impact. By examining buildup and decay effects (Little, 1979), we show that PI has a more immediate predictive relationship with consumers' funding behavior than eWOM. However, while the effects of PI diminish rather quickly, the effects of eWOM persist longer. Although previous studies also explored the differential effects of early versus late eWOM (e.g., (Godes and Mayzlin, 2004; Luo, 2009)), ours is among the first to disentangle and compare the dynamic relationships of opinion-based (eWOM) as well as action-based (PI) online social interactions over time. Second, our study also contributes to the burgeoning software platform literature because we unravel both within-platform and cross-platform dynamics (i.e., between crowdfunding and social media platforms). With rare exceptions (e.g., (Chen et al., 2015; Dewan and Ramaprasad, 2014; Luo and Zhang, 2013)), previous research studied the dynamic effects of eWOM and/or PI on a single platform, overlooking the increasing relevance of cross-platform effects. By addressing these effects, we respond to calls in prior research that emphasize the importance of capturing and unpacking the evolution and interrelationships of multiple time series across information systems and platforms in an increasingly interconnected IT world (Adomavicius et al., 2012). Third, our study contributes to the emerging crowdfunding literature (Agrawal et al., 2015; Belleflamme et al., 2014; Burtch et al., 2013; Mollick, 2014) by showing that both eWOM and previous funding behavior by the crowdfunding community (as indicated by PI) are perceived as quality indicators that allow potential backers to reduce their own risk in the face of uncertainty. Finally, understanding the relative predictive value of eWOM and PI concerning the effect on critical consumer decisions over time can help platform providers and third-party complementors to monitor and analyze the echo of changes in eWOM and previous contribution behavior. They can then adapt their project campaign and communication with prospective consumers accordingly.

3.2 Theoretical Background

3.2.1 Dynamics on Reward-based Crowdfunding Platforms

Crowdfunding, which builds on the broader concept of crowdsourcing (e.g., (Bayus, 2013)), 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 (the fundraisers) to collect contributions (hereafter also referred to as backing or funding a campaign) from a large number of project backers (the funders) through an open call—mostly on the Internet (Schwienbacher and Larralde, 2012). The reasons project creators choose crowdfunding are not limited to financial aspects, as the success of the campaign also validates that there is a market for the respective product and the campaigns themselves can also have a certain marketing effect (Burtch et al., 2013; Mollick, 2014).

Unlike equity-based and lending-based crowdfunding platforms, where backers can generate revenue through private equity in the respective company or through interest on the amount invested, reward-based crowdfunding platforms do not offer backers any financial benefits. Instead, they can expect to receive a "*reward*"—a non-financial tangible benefit for their investment (e.g., early and discounted purchase of the product or service). Rewards have a high level of uncertainty as specific conditions have to be met before backers receive their reward. A fundamental condition is that sufficient funds are raised within the pre-arranged campaign runtime. Even though project creators on most reward-based crowdfunding platforms (such as 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 and deliver the rewards. Furthermore, the backer's investment cannot be equated to a purchase, since there is usually no legal obligation for the creator to produce and deliver the reward (Mollick, 2014). Backers can therefore be less certain that they will receive the 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, and can be inspected thoroughly. Previous research has found these rewards to be a central reason for backers to participate in reward-based crowdfunding (Kuppuswamy and Bayus, 2014).

The primary source of information for a potential backer to use for decision support is the campaign description the creator published on the platform. This often includes a short video, showing the creator, possibly a 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 offered rewards, this quality assessment is potentially biased because all information stems from a single source (the project creator). This means that the quality of the campaign is often relatively vague at the time prospective backers decide whether to pledge. Other evidence concerning the trustworthiness and quality of a campaign therefore becomes increasingly important for potential backers' evaluation. The two most prominent and salient quality criteria that are increasingly available on these platforms are social information, mostly in the form of eWOM cues (e.g., social plugins that display the number of shares the campaign receives on Facebook or the number of direct consumer comments) and popularity information such as prior contribution behavior (e.g., the number of consumers who backed a project is prominently placed on each campaign's dashboard), allowing consumers to observe other consumers' actions (e.g., (Luo and Zhang, 2013; Shi and Whinston, 2013; Duan et al., 2009)).

While previous studies examined the effects of online social interactions on consumer decision-making in settings where the products share characteristics with rewards in reward-based crowdfunding (e.g., the utility of the product is difficult to ascertain before purchase), the concept of reward-based crowdfunding offers unique characteristics that make studying the effects of online social interactions in this setting particularly interesting. First, in other settings, the decision-making processes of consumers are often sequential in that consumers buy, experience, and review products and then influence other consumers. However, in reward-based crowdfunding, experiencing the product is a downstream process that occurs long after the campaign has ended. Therefore, backers influence potential backers with their opinions and actions without having any additional information about the reward. Second, many online platforms such as online auction websites encourage sellers to build and maintain a reputation on the platform as a quality indicator for subsequent buyers. As a crowdfunding campaign is most often a one-off process for the project creators[1], similar reputation mechanisms cannot be found on crowdfunding platforms, which increases the relevance of online social interactions in this setting.

3.2.2 Electronic Word-of-Mouth

Word-of-mouth (WOM) is opinion-based or preference-based social interaction between not commercially affiliated consumers about commercial content such as brands, products, or services (Arndt, 1967; Chen et al., 2011). Previous research found a significant influence of WOM on consumers' information search, evaluation, and decision-making, as it *"influences attitudes during the pre-choice evaluation of alternative service providers"* (Buttle, 1998, p. 242). Furthermore, it has been shown that WOM can be more relevant than traditional marketing channels, such as advertising, in raising awareness about innovation and in convincing the receiver to try out new products (Buttle, 1998). One of the central reasons for the success of WOM is increased perceived reliability, credibility, and trustworthiness compared to communication initiated by organizations themselves (Brown et al., 2007; Arndt, 1967).

The Internet 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 the Internet allows eWOM to spread in an unprecedented speed and scale compared to traditional (face-to-face) WOM, it brings new challenges, such as *"the volatile nature of online identities and near complete absence of contextual cues"* (Jensen et al., 2013, p. 295; Dellarocas, 2003). Still, it has been argued that the consumer motives that have been identified as relevant for traditional WOM are also relevant for eWOM (Hennig-Thurau et al., 2004). According to Hennig-Thurau et al. (2004, p. 39), 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 opinions, preferences, or experiences online are manifold and a multitude of possible channels such as product review websites, blogs, and online communities are available. Due to their constant presence and accessibility, social networking websites such as Facebook in particular have been used to generate massive amounts of eWOM messages.

The response of an individual 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 (Liu, 2006). Only after the receiver is aware of the content, a cognitive process starts evaluating the message's credibility by examining its valence and the receiver's social ties with the sender. Several studies have shown that eWOM volume, rather than

[1] In our dataset, less than 7% of creators had set up more than two campaigns in the past. Out of the top 20 Indiegogo campaigns, 17 were from first-time creators.

valence, is significantly associated with product sales (e.g., (Davis and Khazanchi, 2008; Duan et al., 2008)).

Given the findings on the effects of eWOM on a firm's equity value (Luo and Zhang, 2013; Luo et al., 2013) and on the decision-making of consumers in different contexts such as movies (Liu, 2006), books (Chevalier and Mayzlin, 2006), and video games (Zhu and Zhang, 2010), and taking into account the relatively high risk when investing in crowdfunding campaigns, eWOM can be expected to be of great importance for the success of a crowdfunding campaign. Spreading the word in social media raises awareness for the respective crowdfunding campaign without requiring financial investments and can be central in persuading prospective backers to invest. Without eWOM, the campaign description remains the central source of information for the backer who might be uncertain about the utility of the proposed project and its rewards.

Although eWOM and its contagious effect on consumer decision-making have been extensively investigated in online environments (e.g., (Jabr and Zheng, 2014)), previous research paid only little attention to the fact that eWOM does not unfold in a vacuum. But it may be presumed to occur with parallel observational mechanisms on platforms—that is, besides spreading the word around crowdfunding campaigns, prospective backers can increasingly observe the dynamics of real funding behavior from other backers on the platform.

3.2.3 Popularity Information and Informational Cascades

Compared to eWOM, which is focused on the exchange of information in the form of opinions among consumers, PI facilitates action-based or behavior-based social interactions (Chen et al., 2011; Godes et al., 2005). Many e-commerce vendors use PI cues as an indicator of the choices earlier adopters made by displaying sales rankings or absolute sales in order to influence consumers' choices and behavior. Such observable actions can help consumers to learn what the most appropriate response is in a given situation, because people, in part, *"determine what is correct by finding out what other people think is correct"* (Cialdini, 2009, p. 152). A possible outcome of such behavior is that many individuals start to behave identically. Ultimately, this behavior can lead to informational cascades, an information-based explanation for herd behavior (Bikhchandani et al., 1998; Huck and Oechssler, 2000). Informational cascades occur when individuals who face identical decisions under uncertainty, can observe the actions of other individuals who faced the same decisions earlier on, but not the motivation behind their actions (Bikhchandani et al., 1992; Bikhchandani et al., 1998). In these situations, individuals will consider their own private information as well as the inferences drawn from observing predecessors' decisions. As soon as individuals consider the decisions of other individuals as more informative than their own private information, they will most likely disregard their own information and imitate predecessors' actions in order to overcome uncertainty and to avoid blame from others for making a particular choice (Sun, 2013). Any immediate successors will have even more reasons to disregard their own private information.

Previous IS research showed that, due to large amounts of information available about the purchase decisions of consumers online, the Internet is the ideal environment for this type of herd behavior. Informational cascades have, for example, been found to arise online microloan markets (Zhang and Liu, 2012), when adopting software (Duan et al., 2009), and during online auctions (Simonsohn and Ariely, 2008).

Informational cascades can also be considered a central driving mechanism to explain the behavior of backers on reward-based crowdfunding platforms for the following reasons. First, backers on these platforms face decisions under uncertainty when they decide whether to pledge for a campaign. The uniqueness of the campaigns on these platforms stresses this point, as backers will rarely have to choose between two similar campaigns running simultaneously (Kuppuswamy and Bayus, 2014). Second, the value of the promised reward remains relatively vague at the time the investment decision has to be made, so backers are unable to ascertain the true value until after the delivery when the campaign has ended—similar to experience goods (Shi and Whinston, 2013). Third, crowdfunding platforms are designed so that it becomes very convenient for potential backers to observe the level of funding by other backers at any time during the campaign runtime. Fourth, even though the pledge of any predecessor indicates their actions, the motives behind these actions are not revealed.

Although both types of social interactions have been shown to affect consumers' decision-making processes (e.g., (Chen et al., 2011)), they can be considered distinct influencing mechanisms, as they differ strongly in respect to various characteristics (see Appendix 1 for a detailed overview of these characteristics). For instance, while eWOM messages largely contain qualitative information in the form of opinions about products and discrete buying recommendations, informational cues depicting a product's popularity contain mostly quantitative information (e.g., the number of backers who invested in a specific crowdfunding campaign). Despite their lower information content, PI cues might be more relevant for consumers, as they typically depict definite and consequential actions (Chen et al., 2011). As such, when in doubt about the quality of a product, one person who buys the product might send a stronger signal than a good friend who simply recommends the product without investing in it. However, even though the number of previous backers enables prospective backers to infer the success of the campaign directly, it does not offer any information about the prospective backer's strength of relationship with previous backers. Therefore, for individuals who consider their social network when making an investment, it might be more appropriate to use eWOM for decision support.

Given the distinct, yet complementary nature of both mechanisms in influencing consumers' decision-making processes, it is surprising to find that previous research has so far mainly focused on examining their effects in isolation without considering the mutual interdependencies over time. Particularly in multi-sided markets with high information transparency and a growing integration of social media cues, the effects of eWOM and PI are not detached from one another, but are interwoven and influence each other. Self-reinforcing as well as reciprocal time-varying effects are therefore worth investigating.

3.3 Research Model and Hypotheses Development

Against this backdrop, our research model (Figure 4) incorporates hypotheses that emphasize the dynamic relationships of opinion-based as well as behavior-based online social interactions over time. First, Hypotheses 1 and 3 focus on the self-reinforcing, intra-platform effects (i.e., on social media and crowdfunding platforms respectively) that shed light on how previous eWOM surrounding a crowdfunding campaign drives present eWOM on the respective platform as well as how popularity information in the form of previous funding decisions affects current funding behavior (also called autoregressive carryover effects). Second, Hypothesis 2 captures potential cross-platform and intra-platform effects of eWOM on funding behavior. Finally, Hypotheses 4a/b are derived to theorize the time-varying (i.e., buildup and decay) effects of eWOM and popularity information on the decision-making of backers. We derive the first sets of hypotheses, H1 and H2, drawing on theory related to eWOM effectiveness. We then develop H3 and H4a/b based on the literature related to informational cascades.

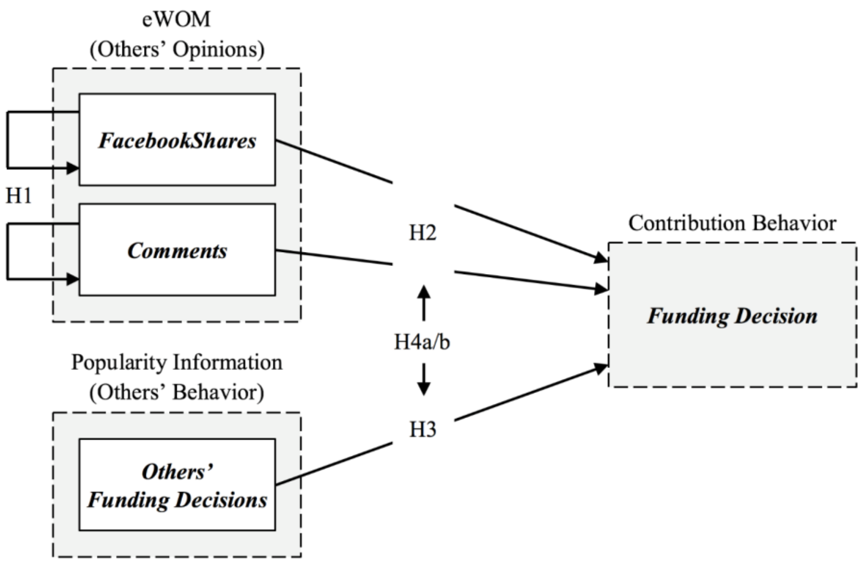


Figure 4: Research Model

3.3.1 Effects of Crowdfunding-Related eWOM

The effectiveness of eWOM describes the ability of eWOM messages to influence a receiver's behavior, as simply receiving a persuasive message may not coincide with an actual response (Cheung and Thadani, 2012). In this study, we distinguish between two outcomes of effective eWOM that could arise after receiving an eWOM message about a specific crowdfunding campaign. First, consumers might join the conversation around the campaign by retransmitting the message on social media or by writing comments about the campaign directly on the platform. Second, consumers might invest financially in the respective crowdfunding campaign. We expect these two outcomes to be sequential in their timing and to differ in their magnitude, due to different motives and risks associated with them. Generally, backers can be expected to have different motives for writing or sharing eWOM messages before and after investing in a crowdfunding campaign.

Before investing, backers are likely to seek peer evaluation by sharing or writing eWOM messages and by evaluating the responses in order to partially compensate for the uncertainty associated with the investment decision. This is consistent with the findings of King and Balasubramanian (1994), showing that other-based preference formation is particularly important for goods which value is difficult to ascertain before purchase (Dewan and Ramaprasad, 2014), making peer evaluation a vital component for the decision-making of a potential backer.

After investing, backers can be expected to write or share eWOM messages for two reasons. First, for self-representation or self-enhancement purposes (Wojnicki and Godes, 2008), where backers share content because it may reflect favorably on them as a sender (Berger and Milkman, 2012). Projects on reward-based crowdfunding platforms are often technically innovative, socially responsible, or very creative, and are therefore ideal to reflect positively on the sender when shared via social media (Adler, 2011). This motive will be particularly relevant for backers who share messages about their recent investments in crowdfunding campaigns on social media, where they usually have established social networks that might not exist between rather anonymous consumers on the crowdfunding platform. Second, as crowdfunding campaigns on Indiegogo will only have the chance to become successful if sufficient funds are raised, it is reasonable for backers to encourage their peers to also invest in the project by sharing the respective crowdfunding campaign via social media.

These motives for writing and retransmitting messages can be expected to be critical for the diffusion of eWOM surrounding specific campaigns. Since it has been shown that a single eWOM message potentially influences a multitude of receivers (Lau and Ng, 2001), we expect that an increase in consumer comments on a crowdfunding platform and in the number of shares on social media will generate additional eWOM on the respective platform in a following period, creating positive feedback loops around a specific crowdfunding campaign[2]. We therefore hypothesize that:

> ***H1****: Past eWOM around a given crowdfunding campaign is positively associated with present eWOM on the respective platform.*

Previous research highlighted the importance of eWOM in the diffusion of new products (e.g., (Arndt, 1967; Mahajan et al., 1984)). It has been argued that with higher perceived risk associated with the early adoption of new products, consumers tend to rely more on eWOM, as it is perceived to be more reliable, credible, and trustworthy compared to communication initiated by organizations themselves (Arndt, 1967; Brown et al., 2007). As mentioned above, crowdfunding is different from a regular buying situation, as the investment is often required without an existing product or service, which increases perceived risk and the importance of eWOM

[2] While the focus of our paper is not on theorizing the differential effects of eWOM based on Facebook shares and comments on Indiegogo, we present notable differences in their effects in the results and discussion sections.

messages. We therefore expect that increasing eWOM on both the crowdfunding platform (comments) and via social media (Facebook shares) will positively influence prospective backers' contribution behavior and promote their funding decisions:

> ***H2**: Past eWOM is positively associated with prospective backers' present funding decisions for a given crowdfunding campaign.*

3.3.2 Informational Cascades on Crowdfunding Platforms

Informational cascades may occur frequently on crowdfunding platforms, as the only available source of information is the campaign description the project creator published, which might be limited in scope, imperfect, or biased. Prospective backers thus often infer the product's utility by observing prior contribution behavior, for example based on popularity information displayed on the platform (e.g., in the form of the number of previous backers or the amount that has already been invested). Popularity information has been found to have a positive influence on consumer adoption decisions and subsequent sales performance (e.g., in the context of online software adoption (Duan et al., 2009) and for niche products (Tucker and Zhang, 2011).

In the crowdfunding context, previous research on the effect of prior contribution behavior on the decision-making of prospective backers has found that for donation-based crowdfunding, the marginal utility 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 when others have already supported the campaign, leading to negative downward informational cascades and ultimately a stagnation of contribution. On the other hand, in equity-based and lending-based crowdfunding markets, backers rather invest in projects that already have a lot of support, which signals superior quality. 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). Already popular campaigns therefore receive an additional popularity boost, leading to positive informational cascades. To our best knowledge, this 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. We hypothesize that the intentions of backers in reward-based crowdfunding markets are more similar to those in equity-based and lending-based crowdfunding markets, as receiving the return on the investment is a primary objective in all three markets (Kuppuswamy and Bayus, 2014). However, the risk of not receiving the reward in reward-based crowdfunding might be rather high, as the funds invested in an unsuccessful project are not reimbursed. Consequently, project creators whose campaigns do not reach the designated funding goal will still receive the funds, but might be unable to deliver the promised rewards to the backers due to a lack of funding. Hence, prospective backers are likely to minimize their risk of pledging without receiving a reward and invest in campaigns that are already on their way to becoming successful in terms of the number of backers, leading to a reinforcement effect on the crowdfunding platform. We therefore expect to identify positive informational cascades and propose that:

> ***H3**: Past funding decisions of other backers as indicated by PI are positively associated with prospective backers' present funding decisions for a given campaign.*

Although we expect that both past eWOM and PI will be positively associated with prospective backers' present funding decisions, it can be assumed that the buildup and decay effects of both types of social interactions will differ strongly. Prior research suggests that decisions that involve bandwagon or herding behavior are associated with short decision times rather than longer ones, which suggests that the propensity to herd is either an instinctive, emotional response and/or that it is a well-practiced, automated decision-making heuristic (Kuan et al., 2014; Baddeley, 2010). Similarly, research on informational cascades found that the phenomenon can help to explain *"rapid and short-lived fluctuations such as fads, fashions, booms, and crashes*" (Bikhchandani et al., 1992) and that, if informational cascades occur, consumers' product choices exhibit significant jumps and drops that are directly associated with the product's popularity (Duan et al., 2009). The rapid and direct response of consumers to the changing popularity of products therefore suggests that an informational cascade, like herding behavior, is triggered by an affective response of the backer, which is usually evoked much quicker than a cognitive response because feelings are often elicited immediately on exposure to a new stimulus (Pham, 1998; Kuan et al., 2014). We therefore expect that the effects of popularity information on the funding decisions of prospective backers show a quick buildup but a short decay. In contrast, although eWOM like advertising messages can evoke affective responses through, for example, emotional content, these responses are combined with cognitive responses (i.e., rational evaluation) to form an attitude toward the message (Wright, 1973; Batra and Ray, 1986). Compared to the affective factors, cognitive factors also typically induce more lasting responses by consumers (Fang et al., 2013).

Additionally, prior research also highlighted that significant delays (wear-in effects) exist between the occurrence of an eWOM message and its impact on consumer decision-making (Luo, 2009). These delays can be explained with the information gathering process that takes place when evaluating eWOM messages. While informational cascades lead to an immediate response because private information is ignored, eWOM messages trigger an information gathering process, helping the individual to form an opinion about a specific crowdfunding campaign. Those who already possess a high degree of expertise would typically devote little effort to an information search prior to purchase (Bloch et al., 1986), meaning that in our context, due to the little information available from other sources, we can expect backers to invest more effort in gathering information via eWOM messages. While this process takes more time, leading to a slow buildup of the effect of eWOM, the outcome is an informed decision that is likely to have a longer lasting effect. We therefore hypothesize:

> ***H4a**: The impact of past funding decisions of other backers as indicated by PI on prospective backers' present funding decisions has a faster buildup than that of past eWOM.*

***H4b**: The impact of past funding decisions of other backers as indicated by PI on prospective backers' present funding decisions has a shorter decay than that of past eWOM.*

3.4 Research Methodology

3.4.1 Dataset and Descriptive Statistics

We collected daily project-level data from Indiegogo, which is among the largest and most prominent reward-based crowdfunding platforms on the web. Since its launch in 2008, more than 400,000 campaigns have run on the platform (Mearian, 2016). Indiegogo offers an appealing context in which to study our research model. The platform offers opportunities for consumers to create and share eWOM messages about the crowdfunding campaigns and reveals PI by prominently depicting the number of previous backers for any campaign on a visual dashboard. The transparent recording of eWOM and previous backers over time opens a window into the reciprocal and dynamic effects of these mechanisms, providing researchers an unobtrusive trace of these often hard-to-study activities. Our data covers 213 days from November 15, 2013 to June 16, 2014, resulting in 23,340 campaigns and approximately 464,000 data points. Data on every campaign that started and ended in this timeframe was gathered automatically in a daily routine with a self-developed web crawler to retrieve time-series data of all campaigns on the website. To account for potential deadline and commiseration effects, we only analyzed campaigns that were covered during their complete lifecycle (Kuppuswamy and Bayus, 2014). Since our dataset spans approximately seven months (including the holiday season), we also checked for seasonality effects, but did not find any significant deviations from the overall pattern. In addition to the number of backers and the specific eWOM volume for each campaign, we collected further campaign-related information (i.e., campaign category, number of campaigns in the respective categories, number of campaign updates, total funding amount in US dollar, campaign runtime in days, and a dummy whether the campaign description contained a video) for robustness checks and ancillary post-hoc subsample analyses (§5.4). To operationalize PI, we chose the number of previous backers of the campaign. The metric is consistent with earlier studies of popularity information in IS and management research, where download numbers or the number of clicks were used as measurements (Tucker and Zhang, 2011; Duan et al., 2009). The number of previous backers is however also distinct from prior operationalizations because it reflects and indicates real financial involvement. We operationalize two types of eWOM: Facebook shares and comments about a project on the crowdfunding platform. As we focus on analyzing eWOM volume, rather than its valence[3], we counted how

3 We argue that in reward-based crowdfunding, analyzing eWOM volume is more appropriate than eWOM valence, given that consumers write their eWOM messages when the reward (e.g., the product being funded and still under development) has not been received yet. It is therefore unlikely that the backer will have had a negative experience with the reward or the project before writing the message. The appearance of many and extreme negative eWOM messages is therefore unlikely. We checked and verified the important assumption that the valence of eWOM messages shared on crowdfunding platforms is mostly positive or neutral, such that we believe a focus on eWOM volume rather than valence is warranted in our study context (Appendix 2). In addition, as negative shares would not generate additional backers, our approach underestimates the true effect, as we treat all shares and comments equally.

often a campaign was shared on Facebook and how many comments were written about it on Indiegogo. Consistent with the metric Tirunillai and Tellis (2012) used, we employ the number of comments users posted about the focal campaign. This measure reflects the magnitude of eWOM received on the crowdfunding platform[4].

As the eWOM volume for Facebook could not be extracted directly from the campaign webpage with our web crawler, we collected the data for the number of shares a specific campaign received via the application programming interface (API) of Facebook. Consistent with previous eWOM studies (e.g.(Toubia and Stephen, 2013)), we collected daily data (i.e., the recording interval is 24 hours (Zaheer et al., 1999) on the number of Facebook shares and comments about the project.

To measure eWOM volume on Facebook around crowdfunding campaigns correctly, we only considered shares that contained a direct hyperlink to the crowdfunding campaign on Indiegogo, as typically used in social media studies (e.g., (Galuba et al., 2010)). To ensure that only genuine Facebook shares were considered for our analysis, we excluded campaigns that showed unnatural peaks in the number of shares on a single day, as they imply fraudulent behavior (Facebook, 2015). Even though peaks in these performance indicators are to be expected when a campaign receives major attention in other channels such as blogs or news websites, these natural peaks are followed by a gradual decline. On the contrary, unnatural peaks do not show these subsequent effects, implying fraudulent actions which would have distorted the results (Facebook, 2015). These unnatural peaks were identified if, on a single day, the number of additional shares exceeded the threefold standard deviation and at least 500 shares were added, which is usually the lowest quantity of fake shares that can be bought (Steuer, 2013a)[5]. The reversed procedure was applied again to ensure that a significant drop in the additional number of shares occurred. Only campaigns that showed an unnatural peak and decline afterwards were dropped from the dataset, resulting in a removal of 429 campaigns. Finally, consistent with standard outlier analysis procedures (Aggarwal, 2013) and previous crowdfunding studies (Wessel et al., 2016), we dropped the top 1% of campaigns with regard to the number of backers and eWOM, as extreme outliers and blockbuster campaigns are expected to show different patterns with regard to their funding process. Summary statistics are presented in Table 2.

[4] As the average number of comments reported in Table 2 might be driven by many zeros in the data, we ran four robustness checks that excluded projects with less than 2, 3, 4, or 5 comments to account for possible skewness. The results did not significantly deviate from our main model.

5 As a robustness check, we conducted the outlier analysis with various alternative threshold values for identifying unnatural peaks, but the results remained qualitatively unchanged.

Table 2: Summary Statistics

	Mean	SD	Min	Max
Backers	28.30925	39.75949	2	420
FacebookShares	192.1488	266.2012	0	2,327
Comments	4.587832	4.862755	0	60
CategoryCompetition (HHI)	0.0479004	0.0704678	0.0052532	1
ProjectUpdates	1.663753	4.889731	0	496
IndiegogoTweet	0.004156	0.064334	0	1
FundingAmount ($)	2,167.6	4,086.464	0	89,234
Video (dummy is 1 if the campaign contains a video)	0.43509	0.4957794	0	1
SuccessProbability	0.1721508	0.3775196	0	1

Note: N (projects) = 23,340; Entries are means at the end of the campaign runtime. IndiegogoTweet is a dummy of whether the platform tweeted about the campaign during the runtime

3.4.2 PVAR Model Specification

We employed a panel vector autoregression (Panel VAR) model to capture the dynamic interdependencies and feedback effects among multiple time series (Dekimpe and Hanssens, 1995). PVAR models are particularly 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). Further advantages of PVAR over alternative models are that it can explicitly *"account for biases, such as endogeneity, autocorrelations, omitted variables, and reversed causality"* (Luo and Zhang, 2013, p. 223). The endogenous treatment of the variables in PVAR models implicate that eWOM and PI are explained by past variables of themselves (i.e., autoregressive carry-over or self-reinforcing effects) as well as past variables of each other (i.e., cross or reciprocal effects) (Luo et al., 2013). The PVAR model also allows capturing complex feedback effects that may encompass the reverse effects of consumers' funding behavior on future eWOM, revealing complex chained effects involving cyclical interactions within and between online platforms. PVAR models have been used particularly in marketing and finance studies (e.g., (Love and Zicchino, 2006; Tirunillai and Tellis, 2012)), while IS researchers only recently adopted them (e.g., (Chen et al., 2015; Dewan and Ramaprasad, 2014)).

The main challenges of our model setup are the simultaneous mutual influences of the different variables of interest, namely the PI and the volume of eWOM. 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., number of backers) to an orthogonal shock of one standard deviation in another variable of interest (e.g., number of Facebook shares) in the current period. By orthogonalizing the response, we can identify the effect of one shock at a time, while holding other shocks constant. This technique combines the traditional VAR approach that treats all the variables in the system as endogenous with the panel-data approach that allows for unobserved individual heterogeneity (Love and Zicchino, 2006). When applying the VAR procedure to panel data, a specific restriction must be imposed. The underlying structure must be the same for each cross-sectional unit and since this constraint is likely to be violated in practice, fixed effects are typically introduced (Arellano and Bover, 1995; Love and Zicchino, 2006). As the fixed effects are correlated with the regressors due to the lags of the dependent variables, and consistent with previous PVAR studies (Love and Zicchino, 2006), we use forward mean-differencing, also referred to as the *Helmert procedure* (Arellano and Bover, 1995). This procedure removes fixed effects by subtracting the mean of all future observations and preserves the orthogonality between transformed variables and lagged regressors. The lagged regressors can then be used as instruments in the PVAR model for the forward-differenced variables to address a possible simultaneity problem (Dewan and Ramaprasad, 2014). As previous studies showed that the within-group estimator (i.e., the least-squares estimator) for fixed effects models is biased when applied to estimate a dynamic panel model, we use generalized method of moments (GMM) to estimate the PVAR model, allowing for error correlation across equations (Love and Zicchino, 2006). Our PVAR model is specified for each crowdfunding campaign as follows:

$$\begin{bmatrix} \mathrm{Backers}_t \\ \mathrm{FacebookShares}_t \\ \mathrm{Comments}_t \end{bmatrix} = \sum_{j=1}^{J} \begin{bmatrix} \beta_{11}^{t\text{-}j} & \beta_{12}^{t\text{-}j} & \beta_{13}^{t\text{-}j} \\ \beta_{21}^{t\text{-}j} & \beta_{22}^{t\text{-}j} & \beta_{23}^{t\text{-}j} \\ \beta_{31}^{t\text{-}j} & \beta_{32}^{t\text{-}j} & \beta_{33}^{t\text{-}j} \end{bmatrix} \begin{bmatrix} \mathrm{Backers}_{t\text{-}j} \\ \mathrm{FacebookShares}_{t\text{-}j} \\ \mathrm{Comments}_{t\text{-}j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{\mathrm{Backers},t} \\ \varepsilon_{\mathrm{FacebookShares},t} \\ \varepsilon_{\mathrm{Comments},t} \end{bmatrix} \quad (1)$$

where $Backers_t$, $FacebookShares_t$, and $Comments_t$ are our endogenous variables and denote the number of backers of a project, the number of Facebook shares, and the number of comments on day $t (t = 1, 2, \ldots, T)$, respectively.

In our PVAR analysis, today's backers[6] are a function of past shares on Facebook, past comments, past backers, and an error term. In the PVAR model, the β-coefficients represent the

[6] We deliberately chose the number of backers as the measure for backers' decision-making behavior instead of the funding amount for several reasons. First, using the number of backers more adequately reflects backers' decision-making behavior and the dynamic relationships among the endogenous variables in the PVAR model because funding amounts may be distorted in several ways (e.g., if backers who are closely related to the project creator donate excessive amounts to the project; individual funding amounts are also arguably driven by the distinct rewards a project offers). Second, in the long run, knowing how many individuals are interested in a specific crowdfunding project and the respective product or service could be more relevant to the creator of the project than reaching a short-term financial goal. Third, using backers instead of funding amounts ensures that all three variables in the PVAR model are measured on the same ordinal scale. Finally, as a robustness check, we conducted the PVAR analysis with funding amounts (in US dollar) as a substitute for the number of backers and obtained qualitatively consistent results.

relationship between the lagged values of each variable and the variable on the left side of the equation. *J* represents the order or lag length of the model, which is usually determined using Akaike's information criterion (AIC) and the moment model selection criteria (MMSC) that Andrews and Lu (2001) developed. Following the standard approach in the VAR literature (Love and Zicchino, 2006; Holtz-Eakin et al., 1988; Andrews and Lu, 2001), we calculated the AIC and the MMSC for each cross-section and took the modal value of the optimal lag among all cross-sections, leading to an optimal lag length of 1.

We also controlled for a set of time-varying, exogenous control variables in our model, including the competition in campaign categories, the number of updates the project creator published during the campaign runtime and unobservable marketing efforts by the platform by monitoring their Twitter activity as a proxy. First, we controlled for the concentration of campaigns in each category to account for the competition (i.e., prospective backers' attention allocation) that a project faces in its primary target category (Hansen and Haas, 2001). We used the following Herfindahl-Hirschman Index (HHI) as measure:

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

where b_i is the fraction of a project's number of backers in the ith project category on Indiegogo at time t. This measure ranges from $1/N$ to 1, where N is the number of projects in a given category. The HHI ranges from 0 to 1, were 1 represents a monopolistic market, and a decreasing index indicates stronger competition (Hansen and Haas, 2001). For example, if a project has all backers in the category *Technology*, this measure is 1 and it is maximally concentrated. A decreasing index therefore indicates stronger competition. Second, postings of project updates (e.g., progress updates, answers to questions, or appreciation messages) on the campaign website by the project creator may influence investor confidence. We therefore controlled for project updates measured as the cumulative number of updates posted on a project website since the start of the campaign (Kuppuswamy and Bayus, 2014). Third, we monitored Indiegogo's Twitter account to identify campaigns that benefited from potential marketing efforts by the platform providers. We used a dummy variable to mark the exact day when a campaign was mentioned on Indiegogo's Twitter account.

3.5 Results

3.5.1 Test for Stationarity in Time Series and Granger-Causality

The procedure of estimating PVAR models typically starts with a unit-root test to assess whether variables are evolving or stationary (Luo et al., 2013). Stationarity is an important assumption to check in time-series and panel models in order to prevent spurious results. We employed a Phillips-Perron (PP) unit root test, which is a common method in dynamic panel data analysis (Phillips and Perron, 1988). The PP test results suggest stationary time series (see Appendix 3). Next, we conducted pair-wise Granger causality tests to understand the time-based causality in our PVAR model. Granger causality tests help to determine whether the lagged values of one variable help predict values of another variable in the PVAR system (Granger, 1969). More specifically, if a lagged time series a_{t-j} (e.g., $FacebookShares_{t-1}$) improves the accuracy to predict another time series b_t (e.g., $Backers_t$), then a_{t-j} Granger-causes b_t. Table 3 provides the *p*-values and Wald-CHI^2 values for all possible pairwise Granger causality tests related to our estimated PVAR model. Our results suggest that all three endogenous variables have significant temporal-based causal relationships with each other. The two eWOM volume metrics and the PI significantly *"Granger-cause"* each other, providing strong evidence of cross- and reverse causal effects and, ultimately, cyclical interactions between these variables. Solely, *Comments* appear to be unaffected by past *Backers* and *FacebookShares.* As a consequence, these results indicate that modeling the dataset requires a dynamic system that can account for the complex relationships among multiple endogenous variables, supporting our approach of analyzing the variables through PVAR analysis.

Table 3: Granger Causality Tests

	Caused by		
Results	*Backers*	*FacebookShares*	*Comments*
Backers	-	88.776 (0.000)	117.301 (0.000)
FacebookShares	8.592 (0.00)	-	41.499 (0.000)
Comments	0.312 (0.576)	0.228 (0.633)	-

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

3.5.2 PVAR Model Results

To test our research hypotheses, we estimated the coefficients of the endogenous system of variables given in the PVAR model, controlling for category competition, project updates, and Indiegogo Tweets. Results from the analysis are reported in Table 4[7]. Before turning our attention to our first research hypotheses, we report the findings for the three control variables. First, we find that the coefficient estimates on category competition (measured by the HHI) are positive and statistically significant across our three dependent variables, which means that if fewer projects receive more attention, eWOM activity and backings increase. This result points towards the importance of a reinforcement effect. The extreme case would be an evenly distributed number of backers among all projects, which would inhibit PI, as all campaigns are equally popular. Second, the coefficient estimates on project updates is negative and statistically significant for *Backers,* suggesting that posting project updates on a campaign website does not necessarily instantly increase the number of backers of a campaign, as previously stated (Kuppuswamy and Bayus, 2014). Third, we checked whether marketing efforts by Indiegogo for specific campaigns improved their performance. We therefore analyzed all Tweets published by Indiegogo's Twitter account that contained a link to a specific campaign. We find that these efforts by the platform provider might indeed increase the number of backers, even though the effect is only weakly significant.

Table 4: PVAR Model Results for Main Analysis

	Response of dependent variable		
Response to	$Backers_t$	$FacebookShares_t$	$Comments_t$
Endogenous variables			
$Backers_{t-1}$	0.911***	0.0257**	0.000152
$FacebookShares_{t-1}$	0.00193***	0.905***	0.0000226
$Comments_{t-1}$	0.126***	0.538***	0.912***
Exogenous variables			
$CategoryCompetition_{t-1}$	1.967***	36.76***	1.178***
$Updates_{t-1}$	-0.0624***	-0.0841	0.00415
$IndiegogoTweet_{t-1}$	2.381*	2.857	0.188

Note: The PVAR model is estimated by GMM. The reported numbers show the coefficients of regressing the column variables on lags of the row variables. ***, **, * denote significance at 0.1%, 1%, and 5% respectively. N=23,430

[7] As a robustness check, we followed Lin, M. F., Lucas, H. C. and Shmueli, G. (2013b), "Too Big to Fail: Large Samples and the p-Value Problem", *Information Systems Research,* Vol. 24 No. 4, pp. 906-917., who pointed out that studies with large sample sizes should not solely rely on *p*-values, as this might lead to a claim of support for hypotheses with no practical significance. We therefore followed their practice and provide coefficient/*p*-value/sample size (CPS) charts for the PVAR main analysis in Appendix 5 to illustrate that our results are not based on sample size but hold for random subsampling.

We posited in Hypothesis H1 that an increase in eWOM volume leads to additional eWOM volume on the respective platform. We find strong support for this hypothesis, as the coefficient for *FacebookShares* (0.905, $p<0.001$) as well as *Comments* (0.912, $p<0.001$) are strongly significant, implying a substantial reinforcement effect of eWOM.

For Hypothesis H2, we highlight the effects of eWOM on prospective backers' funding behavior. In our model, we are able to estimate the impact of today's *Comments* and *FacebookShares* on tomorrow's number of backers. Our results show that there is a significant and positive effect of present *FacebookShares* (0.00193, $p<0.001$) and *Comments* (0.126, $p<0.001$) on future *Backers*. We therefore find strong support of our hypothesis for Facebook-based as well as comment-based eWOM. This gives us further reason to believe that consumers trust recommendations and information from friends on Facebook as well as from an active discussion by more or less foreign commentators on the platform. Even though both eWOM forms appear to increase the number of backers, the reciprocal effect is different. While we observe an increased number of *FacebookShares* following an increase in backers, this effect does not occur for comments, meaning that backers tend to share their investment decision with their social network, but discontinue discussing it on the platform itself.

Our third hypothesis was based on the argument of informational cascades and proposed that past funding decisions of other backers were positively associated with prospective backers' present funding decisions. We observe a strong positive response of the number of backers (0.911, $p<0.001$) to an increase of their own lagged value (i.e., the observation of the dynamics of other supporters' backing behavior). This positive and significant response lends credence to the argument around positive informational cascades within platforms and suggests a strong self-reinforcement effect arising from observing other consumers' choices, in support of H3.

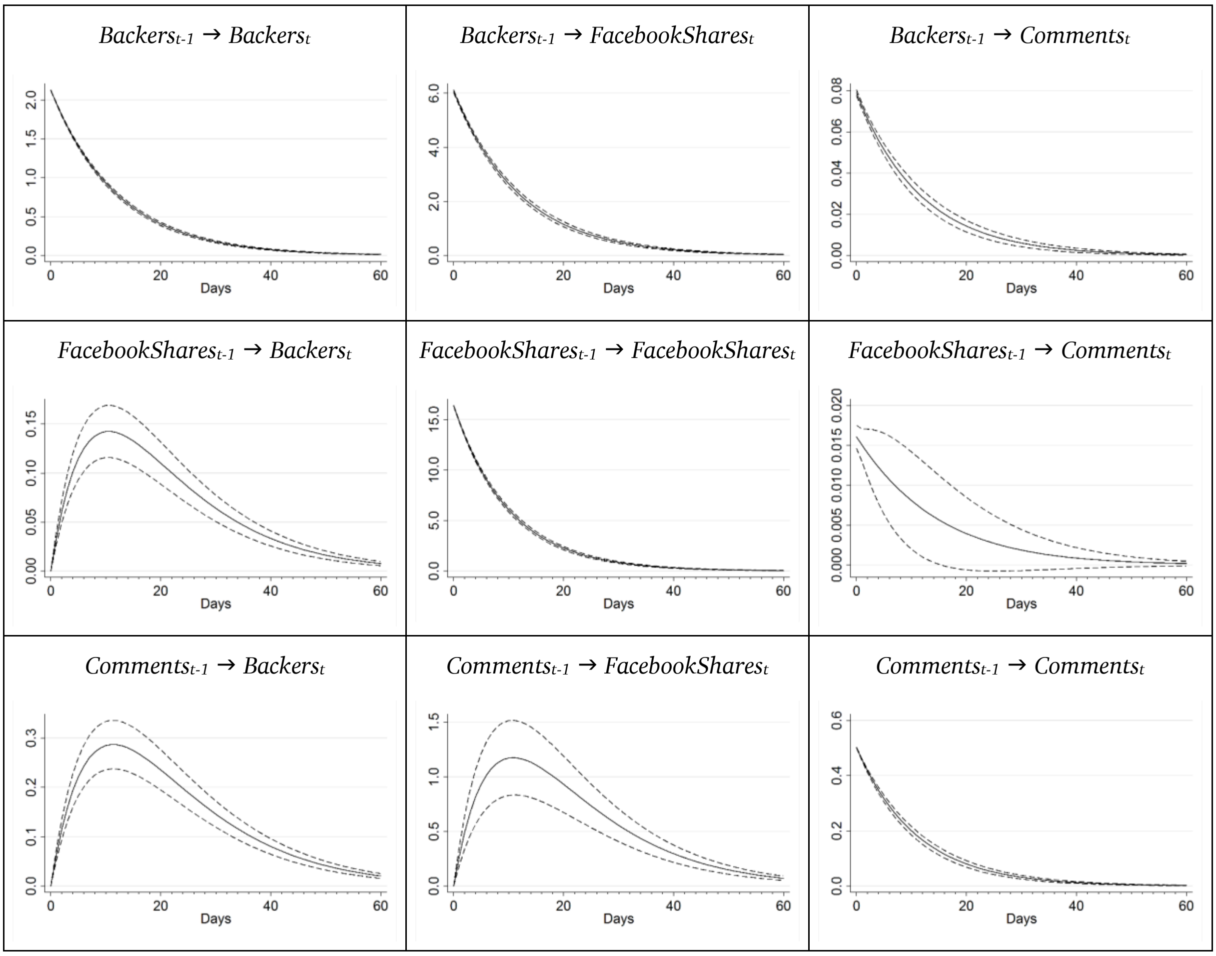
3.5.3 Error Variance Decomposition and Impulse Response Functions

PVAR analyses are usually supplemented with generalized forecast error variance decomposition (GFEVD) and impulse response function (IRF) analyses (Adomavicius et al., 2012; Luo and Zhang, 2013) to gain increased insights about the dynamics in the relationships of interest. GFEVD analysis provides insights into the relative power over time of shocks triggered by each endogenous variable in explaining other endogenous variables of interest in the PVAR model (e.g., prospective backers' funding behavior). It is therefore comparable to a partial R^2 that indicates the percentage of the variance of the error made in forecasting a variable because of specific shocks of all the variables in the system at a specified time horizon (Stock and Watson, 2001).

As such, GFEVD provides indications of the relative importance and magnitude of the effect of each endogenous variable in the PVAR model. The GFEVD analyses shows that for a forecast horizon of 60 days, 6.67% of the variation in the backer variable is explained by the eWOM variables, whereas in the short run with a 10-day horizon only 2.88% is explained. Accordingly, most of the variance in the endogenous variables is explained by their own lags, suggesting a strong feedback loop within each (crowdfunding and social media) platform rather than across them, which is in line with the coefficients from the PVAR analysis (for a more detailed GFEVD analysis see Appendix 4).

The variance decomposition further emphasizes the importance of action-based online social interactions (PI) compared to opinion-based online social interactions (eWOM), showing that the explanatory power of PI is generally stronger compared to eWOM regarding present backing behavior, although the effect of PI appears to be less persistent over time.

We supplemented the PVAR estimates and the GFEDV analyses with an analysis of the corresponding impulse response functions (IRF) for our research model. For our last set of hypotheses (H4a and H4b), we turn to the analysis and interpretation of the IRFs. Figure 5 provides the nine possible IRFs for the estimated PVAR model. Each plot in Figure 5 can be interpreted as depicting the corresponding response (increase or decrease) of a dependent variable over time to a one standard deviation shock in another dependent variable in the preceding period, while keeping all other variables constant (Adomavicius et al., 2012). Using IRFs, we can visualize the dynamics of the pairwise relationships of our research model.



Note: The x-axis is the forecast horizon (in days) and the y-axis is the forecasted response of the dependent variable to a unit shock in the impulse variable. Errors are 5% on each side generated by Monte Carlo simulations with 1,000 repetitions.

Figure 5: Impulse Response Functions (Impulse → Response)

The results of the IRF analysis support the results from the PVAR model and serve as an initial indication for our final hypotheses. All responses are positive and vary in the magnitude of their effects, as depicted in the position of the response function on the IRF plots. While the response of backers is strongest in magnitude when a shock in previous backers (compared to shocks in *FacebookShares* or *Comments*) is triggered (first column of Figure 5), the response in eWOM is greatest when a shock in previous eWOM on the corresponding platform occurs (second and third column of Figure 5). This pattern of results underscores the strengths of self-reinforcing effects on the respective platforms and, in particular, the predominance of the underlying PI for affecting current backing behavior.

In H4 we argued that PI has a fast buildup and a fast decay, compared to eWOM effects that require more time to be effective. We therefore interpret the buildup (i.e., how long it takes for each variable to reach the peak of the predictive relationship with the other variable) and decay (i.e., how long it takes for the predictive relationship to decrease from the peak impact point to non-significance) of the IRF. Additional important insights about the immediacy and persistence of the effects can also be derived and are presented in Table 5 (Fang et al., 2013). The immediate effect denotes the magnitude of the response of backers on the first day after a shock. The cumulative effect is the sum of the response effects over 60 days. The peak effect is the largest effect over time and marks the point of inflection, which concludes the buildup.

Table 5: Timing and Effect Intensity on *Backers*

Effect of	Immediate Effect (SD)	Cumulative Effect (SD)	Relative Fraction of Immediate Effect (%)	Peak Effect (SD)	Buildup Time
Backers	1.957* (0.003)	26.633* (0.413)	7.35%	1.957* (0.003)	1
FacebookShares	0.0336* (0.003)	3.999* (0.409)	0.84%	0.142* (0.024)	11
Comments	0.0630* (0.025)	8.546* (0.783)	0.74%	0.287* (0.029)	11

Note: SD = Standard deviation; Buildup time is measured in days; Effects are calculated with Monte Carlo simulation and 1,000 repetitions; * $p<0.01$

Most notably, while we can observe strong immediate effects in the $Backers_{t-1} \rightarrow Backers_t$ plot that attenuate rather quickly, the effects in the $FacebookShares_{t-1} \rightarrow Backers_t$ plot are less immediate (the buildup time is from day 1 to day 11), yet taper off more slowly, suggesting more persistent effects on consumers' backing behavior. The effects in the $Comments_{t-1} \rightarrow Backers_t$ plot also reach their peak impact point after around 11 days and diminish gradually thereafter. The relative fraction of the immediate effect is ten times higher for PI (7.35%) compared to the immediate eWOM effects (0.84% and 0.74%, respectively). The results also show that eWOM requires a significantly longer buildup time than PI (Kruskal-Wallis test for *Comments* = 4.1 and *FacebookShares* = 23.69, both $p<0.05$). In sum, these results strongly support our final two hypotheses H4a and H4b.

3.5.4 Post-hoc Subsample Analysis

In addition to the full-sample analysis described above, we conducted two sets of post-hoc subsample analyses in order to examine whether the dynamic relationships are consistent for campaigns that are successful vs. unsuccessful[8] and have low vs. high average investment/funding amounts[9]. We chose to investigate how our main results vary for successful and unsuccessful campaigns and for campaigns with low and high average investments, because we expect the effects to be considerably different for successful compared to unsuccessful campaigns and because prospective backers are likely to go through different types of decision processes based on the level of financial commitment (Engel and Blackwell, 1982).

Table 6: PVAR Model Results for Sub-Sample Analyses

	Model (1): Winner	Model (2): Loser	Model (3): High spending	Model (4) Low spending
Response to	Response of dependent variable $Backers_t$			
$Backers_{t-1}$	0.886***	0.922***	0.923***	0.893***
$FacebookShares_{t-1}$	0.00478***	0.00128***	0.00156***	0.00230***
$Comments_{t-1}$	0.337***	0.0469***	0.0700***	0.228***
Response to	Response of dependent variable $FacebookShares_t$			
$Backers_{t-1}$	-0.0448**	0.0736***	0.0365***	0.00891
$FacebookShares_{t-1}$	0.916***	0.900***	0.906***	0.903***
$Comments_{t-1}$	0.770***	0.452***	0.549***	0.571***
Response to	Response of dependent variable $Comments_t$			
$Backers_{t-1}$	-0.00156**	0.000791*	0.000136	0.00021
$FacebookShares_{t-1}$	0.000195*	0.00000251	0.0000641	-0.0000175
$Comments_{t-1}$	0.933***	0.904***	0.919***	0.905***
Response to (Controls)				
$CategoryCompetition_{t-1}$	Included	Included	Included	Included
$Updates_{t-1}$	Included	Included	Included	Included
$IndiegogoTweet_{t-1}$	Included	Included	Included	Included

Note: The PVAR model is estimated by GMM. The reported numbers show the coefficients of regressing the column variables on lags of the row variables. ***, **, * denote significance at 0.1%, 1%, and 5% respectively.

8 Campaigns tend to either surpass their funding goal (they are successful) or fail to do so (they are unsuccessful), by a large margin Mollick, E. (2014), "The dynamics of crowdfunding: An exploratory study", Journal of Business Venturing, Vol. 29 No. 1, pp. 1-16..

9 In order to split the sample based on the average funding amount per campaign, we calculated the average funding amount per backer for each campaign. We then used a median split to turn the continuous variable (average funding amount per campaign) into a categorical one with the values "*low*" and "*high*" spending.

First, we can observe in Models 1 and 2 of the subsample analysis (Table 6) that the relationship regarding the effect of eWOM across and within platforms is much weaker for campaigns that fail to reach their funding goal compared to the successful ones, while the effect of PI within a platform still holds, regardless of campaign success. These results indicate that for crowdfunding campaigns eWOM can be a crucial, if not decisive, success factor, while PI has consistent self-reinforcing effects across all campaigns. Second, with respect to our results regarding the average investment size depicted in Models 3 and 4 of the subsample analysis, we observe that eWOM effects give way to PI effects for higher spending amounts, while eWOM becomes more important for small contributions. This means that action-based online social interactions become particularly important for investment decisions that involve more substantial amounts.

3.6 Discussion

This study was motivated by the observation that—despite the increasing information availability about other consumers' choices and opinions on consumer platforms—we know little about the reciprocal nature of influence among eWOM and PI, and how these mechanisms dynamically and differentially shape consumer decision-making. This paper offers insights into the dynamic interplay between eWOM, PI, and contribution behavior on consumer platforms in the context of crowdfunding. Our overarching finding is that an *"action"* in the form of a past contribution (action-based social interactions) has stronger and more immediate effect on future contribution behavior, and thus speaks louder than spreading the *"word"* about project campaigns via eWOM (opinion-based social interactions). We could also reveal that the impact of a positive shock in previous backing behavior abates relatively fast, while the effects of a positive shock in eWOM decrease at a slower pace.

Two more specific findings in our study are noteworthy. First, we could demonstrate the critical role of eWOM for the outcome of crowdfunding campaigns. As shown in our subsample analysis, subsequent effects of eWOM are weaker for campaigns that fail to reach the desired funding goal, while successful project creators can use the information distribution in social media in full capacity. Also, the relative predictive power of eWOM increases over time, indicating that social media interactions, within and beyond the platform, are a crucial discriminating factor for the success of crowdfunding campaigns. Second, our results based on the subsample analysis differentiating between high and low average funding amounts show that backers rely more heavily on PI when making higher investments. This suggests that backers strive for more informed and fact-based decision-making when faced with a higher investment risk.

3.6.1 Implications for Theory and Research

Our study advances our understanding of the dynamic interplay among social media and critical consumer behavior within and across consumer platforms. First, while previous research, with a few exceptions (Cheung et al., 2014; Chen et al., 2011), focused on examining the effects of eWOM and PI in isolation from one another, our study is among the first to show that both types of social interaction have to be considered together, as they dynamically influence each other and differentially affect consumer decision-making over time. By measuring buildup and decay effects (Little, 1979), we show that PI has a more immediate predictive relationship with consumers' funding behavior than eWOM, but its effects diminish rather quickly, while the effects of eWOM require a longer time to build up their effectiveness but are more persistent over time. These results contribute to the software platform and social media literature by advancing our understanding of PI's and eWOM's temporal effect patterns. We also provide evidence of strong Granger-causal interdependencies that highlight the reciprocal and intertwined nature of influence among eWOM and PI over time, confirming that it is both theoretically and empirically valuable to examine these social interaction mechanisms in combination rather than in isolation. Second, while cross-platform effects have become increasingly important, previous research—with only rare exceptions (e.g., (Chen et al., 2015; Dewan and Ramaprasad, 2014; Luo and Zhang, 2013))—tended to study the dynamic effects of eWOM and/or PI on a single platform (e.g., a software download platform). Our study is one of the first to focus on both within-platform and cross-platform dynamics (i.e., effects occurring between crowdfunding and a social media platform) and how they can affect critical consumer contributions involving real financial consequences. This study therefore answers to calls for research that stress the importance to track and unravel the evolution and interrelationships of multiple time series across information systems and platforms in an increasingly interconnected IT world (Adomavicius et al., 2012; Tiwana et al., 2010). Our study extends previous IS and social media research by going beyond one-directional relationships in fully accounting for the time-varying dynamic effects (i.e., self-reinforcing, cross- and reverse causal effects) in a system of mutually interdependent endogenous variables (Luo et al., 2013). Finally, we contribute to the still nascent yet emerging crowdfunding literature (e.g., (Agrawal et al., 2015; Belleflamme et al., 2014; Burtch et al., 2013; Mollick, 2014)) by showing that in reward-based crowdfunding markets, prospective backers tend to contribute to projects that have already received a lot of attention on social media as well as on the crowdfunding platform itself. This suggests that, similar to equity-based and lending-based crowdfunding markets (Zhang and Liu, 2012; Herzenstein et al., 2011a), and in contrast to donation-based crowdfunding markets (Burtch et al., 2013), prospective backers perceive prior contribution behavior by others as a quality indicator, which allows them to reduce their own risk in the face of uncertainty. However, as we could show in our split-sample analysis, the importance of these quality indicators varies with the investment amount. Furthermore, although herding behavior has been shown to be triggered by non-biased quality indicators in lending-based crowdfunding markets (Zhang and Liu, 2012), our study is the first that compared the time-varying effects of PI and eWOM in a crowdfunding context.

3.6.2 Practical Implications

Our findings offer various practical implications that should be considered, particularly by providers of and third-party complementors (campaign/project creators) on crowdfunding platforms. First, project creators should bear in mind that prospective backers are responsive to changes in PI, which has comparatively stronger and more immediate effects than eWOM. As such, early support from the creator's own network is likely to increase the chances of success further down the road of the campaign. Second, project creators should be aware that eWOM—due to its persistent effect—could make the difference for their campaign's success, as backers often learn about campaigns via their online social networks, spread the word about the campaign via social media, or request feedback on the campaign from peers prior to their own investment. Third, our findings suggest that the spread of eWOM on Indiegogo and Facebook is influenced differently by the decision-making of backers. We find that backers tend to share their investment decision with their social network on Facebook, but are apparently not willing to discuss it afterwards on Indiegogo. Consequently, it is advisable that project creators highlight the favorable aspects of their projects in the campaign descriptions, engage in social media marketing throughout the campaign runtime, and encourage backers to further share the campaign, comment on it on the platform, and keep an active discussion with prospective and past backers. Finally, understanding the relative predictive values of eWOM and PI for critical consumer contributions can help providers of consumer platforms monitor and analyze the impact of changes in eWOM and previous campaign backing behavior over time. Based on real-time evaluation of this information, providers are better able to adapt the salience and granularity of social media cues/metrics as well as information about other consumers' past choices (popularity information) to stimulate contribution behavior and increase platform prosperity overall.

3.7 Limitations, Future Research, and Conclusion

While our study provides several contributions to research and practice, we acknowledge limitations that have to be considered when interpreting the results and implications. In calling attention to these limitations, we hope to suggest avenues for future research. First, although crowdfunding platforms share many characteristics with other multi-sided online consumer platforms, in particular the transparent recording of eWOM and previous consumer activities, caution should be taken when drawing conclusions from our findings. Future research might attempt to confirm the interdependent and dynamic nature of relationships between eWOM, PI, and critical consumer behavior found in this study in other online platform settings (e.g., mobile app or media streaming platforms) besides crowdfunding. Second, we were unable to take into account all types of eWOM that might affect the outcome of crowdfunding campaigns and have therefore limited our analysis to messages spread via Facebook and comments on the platform itself. Future research may benefit from including a broader set of social media (e.g., blogs or social news) and other non-biased quality indicators available to potential backers, such as credit scores of creators that are available on other types of crowdfunding platforms.

Third, our research design can show relationships among endogenous variables, but cannot assure causality. A fruitful avenue for future research is the use of laboratory or randomized field experiments. Our research design is also constrained by the recording unit of 24 hours, which might not perfectly capture the possible simultaneity of the variables. Another approach for future studies would be to reduce the recording unit from days to hours or minutes to better approximate those effects. Fourth, although our sentiment analysis of Facebook shares and comments revealed that eWOM messages with a negative sentiment are rare in the context of crowdfunding, it is worth exploring how eWOM valence interacts with PI and how they jointly affect critical consumer behavior on crowdfunding platforms. Finally, we did not focus on discriminating between different originators of eWOM on Facebook and Indiegogo. The characteristics of different eWOM originators (e.g., number of friends, commercial or private accounts, and experience in crowdfunding) might reveal additional insights.

In conclusion, this study provides an initial step towards understanding the reciprocal and dynamic nature of effects among eWOM, PI, and consumer decision-making. Our central finding is that previous consumer contributions have stronger predictive and more immediate effects than eWOM. eWOM is nonetheless an important complementary influencing mechanism, as its stimulating effects diminish slowly, while the effects of PI decay rather quickly. We hope that our results provide impetus for further analysis of the interdependencies between eWOM, PI, and contribution behavior, and give actionable recommendations to platform providers and project creators in the crowdfunding context.

4 Fake Social Information on Platforms

Title:	A Lie Never Lives to be Old: The Effects of Fake Social Information on Consumer Decision-Making in Crowdfunding (2015)
Authors:	Thies, Ferdinand
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Abstract

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

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

4.1 Introduction

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

An extremely widespread method to reflect consumer opinions in a quantitative manner is the use of social media buttons such as the Facebook Like button, which is present on about 30% of the most popular websites worldwide (Built With, 2014). When placed on a website, the button shows a counter reflecting the number of Facebook users who have previously "liked" this specific webpage or have shared the link to it with their peers (Facebook Inc., 2014). For subsequent visitors to the webpage, the button thus becomes a quality signal with a high number of Facebook Likes reflecting that the content or the offered product is of high quality, interesting or worth sharing for other reasons. However, unlike 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 this limited information content, prior research has shown that quantitative social information can have a substantial influence on the decision-making of consumers (e.g., Duan et al., 2009; Tucker and Zhang, 2011). These studies, however, were focused on ordinal rankings that reflect actual popularity of a specific product among consumers. In contrast, the counter on the Facebook Like button only captures preferences and does not necessarily reflect actual behavior such as how many consumers have bought a product or downloaded specific software. The Facebook Like button thus remains a relatively subjective measure of popularity. Nevertheless, this social information can potentially be of high relevance for consumers in situations in which assessing the quality of specific products is especially difficult (Schöndienst et al., 2012a; Thies et al., 2014). This is particularly true for products and services financed through reward-based crowdfunding platforms such as Kickstarter and Indiegogo. Here, the so-called backers invest in campaigns that appeal to them in the hope to receive adequate tangible rewards for their investment, even though they are not guaranteed legally (Mollick, 2014). In addition to the risk of not receiving a reward at all, the quality of the reward remains unpredictable at the time the investment decision has to be made, because the rewards have not been created yet. Consequently, the utility of the rewards can only be ascertained when receiving them after the campaign has ended, thus increasing the relevance of quality signals such as the Facebook Like button in this setting.

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

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

> ***RQ 1:*** *How does fake social information in the form of Facebook Likes affect the decision-making of backers on crowdfunding platforms?*
>
> ***RQ 2:*** *What circumstances make crowdfunding campaigns more prone to receiving fake Facebook Likes?*

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

4.2 Theoretical Background and Prior Research

4.2.1 Information Asymmetry and Signaling

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

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

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

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

Despite the high relevance of social information as a quality signal for consumers, relatively little prior research exists on biases that may appear in this context. For example, Dellarocas et al. (2010) have found that consumers are more likely to review less available and less successful products in the market but, at the same time, are also more likely to contribute reviews for products that already received a high number of reviews. Furthermore, it has been shown that reviews posted early in a product's lifetime tend to be positively biased (Li and Hitt, 2008). A more substantial and preeminent threat to the credibility and trustworthiness of social information as a quality signal, however, is the possibility of creating fake data (Luca and Zervas, 2013). Even though some governments have reacted to the growing trend of surreptitious advertising through, for example, customer product reviews and these kinds of endorsements and testimonials now have to be classified as such (e.g., Federal Trade Commission, 2009), faking this data is still a growing trend. Consequently, it remains challenging for providers of online services to identify social information that does not reflect genuine consumer opinions or behavior by, for instance, increasing the cost of posting fake content (Mayzlin et al., 2012).

Popular websites such as Yelp.com use algorithms to identify and mark specific reviews as fraudulent (cf., Jindal et al., 2010; Li et al., 2011). On Yelp, fraudulent reviews account for 16% of all reviews and tend to be particularly extreme (either favorable or unfavorable) (Luca and Zervas, 2013). While consumers might be able to identify fake qualitative content due to its extreme nature and exaggerations contained therein, purely quantitative non-genuine content such as a rating is generally more difficult to identify by service providers and especially by consumers. This is a particular challenge in the context of Facebook Likes as a quality signal, as it remains impenetrable to the consumer whether the Likes are a genuine signal sent by other consumers or a non-genuine signal sent by sellers.

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

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

> ***Proposition 1:*** *An artificially created positive shock in the number of Facebook Likes that a crowdfunding campaign receives will lead to an increase in the number of backers pledging for the campaign in the following period.*

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

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

4.2.3 Campaign and Platform Characteristics in Reward-Based Crowdfunding

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

Crowdfunding also offers a variety of incentives for backers to "pledge" for a specific campaign. These incentives mainly depend on the return the backers can expect from their contributions, which range from donations to company equity (Ahlers et al., 2015). On Kickstarter and Indiegogo, the most common and salient type of return is a so-called "reward" that often allows backers to be among the first customers to sample the product or service financed through the campaign. In this study, we focus on this so-called reward-based crowdfunding, as it is by far the most widespread concept of crowdfunding today (Kartaszewicz-Grell et al., 2013).

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

The dynamics of crowdfunding are thus different from those in a traditional e-commerce setting between a seller and a buyer. Backers can be less certain that they will actually receive a return on their investment and have less information about the object they are investing in compared to a regular buying situation, in which the product or service already exists. The primary source of information for a potential backer is the campaign description the creator has published. Even though this content allows prospective backers to develop an attitude towards the campaign and the comprised rewards, this attitude is potentially biased due to the fact that it stems from a single source of information (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.

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

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

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

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

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

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

4.3 Research Methodology

In most cases, creating fake Facebook Likes will be a decision taken and executed by the creators of a specific crowdfunding campaign in the hope to send a quality signal to prospective backers. The shock in the number of Facebook Likes can thus be assumed to be endogenous to the campaign creators but exogenous to the platform providers and the backers (Claussen et al., 2013).

In order to explore the effects of non-genuine Facebook Likes, we employ three different methods. First, we provide descriptive evidence on the distribution of fraudulent behavior on the focal platforms. Second, we investigate the effect of the artificial manipulation using a panel fixed effect negative binominal regression model, treating the purchase of fake Likes as an endogenous shock (Cameron and Trivedi, 2013). Third, we use a probit model with the occurrence of fake Facebook Likes as the binary dependent variable. We are therefore able to assess the influence of the different characteristics of campaigns on the likelihood that manipulation occurs (Finney, 1971; Cameron and Trivedi, 2005).

4.3.1 Dataset and Identification of Campaigns with Fake Likes

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

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

4.3.2 Model

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

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

where y_{it} is the dependent variable describing the additional backers on each day. The individual-effects negative binominal model assumes that y_{it} takes non-negative integer values and is overdispersed. Our independent variable is represented by 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).

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

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

Here y_i is the occurrence of fake Facebook Likes depending on campaign characteristics x_i.

4.3.3 Variables

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

To control for the possibility that additional backers decided to support a campaign because of a crucial update in the campaign description, we included a simple count accumulating each update on a given day. Furthermore, we included a factor variable for each category as a control variable. Summary statistics for our final dataset and all relevant variables are depicted in Table 7. All Summary statistics, except the delta values, show the value of each variable at the end of the campaign life cycle.

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

4.3.4 Robustness Checks

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

4.4 Results

We now present the results of our analysis, starting with the descriptive evidence, followed by the results for the fixed-effects negative binominal regression, and the probit regression. Table 7 provides the summary statistics on a campaign level for all available campaigns and a subset for the manipulated campaigns. We present the results of our main model in Table 8, which provides evidence for the effects of manipulated social information on the backing behavior of the crowdfunding community. We conclude with our probit model in Table 9 to show, what factors of a crowdfunding campaign influence the occurrence of fake Facebook Likes.

4.4.1 Descriptive Evidence

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

Table 7: Summary Statistics for the Complete Dataset and for Campaigns that Received Fake Likes

Complete Dataset	Kickstarter (N= 46,228)				Indiegogo (N=35,370)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Fake Likes (Dummy)	0.019	0.136	0	1	0.036	0.187	0	1
Facebook Likes	350.94	5,040.46	0	862,334	326.08	1,277.31	0	80,227
Backers	97.66	717.08	0	103,971	41.18	234.09	0	13,864
Accum. funding	7,824.19	74,035.03	0	8,878,850	3,203.55	21,616.52	0	1,197,746
Funding goal	45,011.57	1,283,560	1	1.00e+08	86,127.46	7,066,314	250	1.00e+09
Campaign duration	33.25	10.76	6	60	41.78	14.94	6	60
No. of rewards	8.20	6.02	0	227	5.03	4.99	0	179
Video	0.72	0.45	0	1	0.66	0.47	0	1
Updates	2.42	4.50	0	123	2.07	5.98	0	496
Campaigns backed	3.02	14.11	0	1091	1.31	9.78	0	836
Campaigns created	1.40	1.86	1	111	1.26	1.02	1	38
Facebook friends	651	777	0	5,021	.	.	.	.
Team size	.	.	.	.	1.94	1.85	1	48
Concentration	0.044	0.048	0.0034	0.6595	0.038	0.060	0.004	1
Crowdedness	1.06	0.49	0.033	2.23	0.933	0.575	0.002	2.23
Fake Likes	**Kickstarter (N=874)**				**Indiegogo (N=1,287)**			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Facebook Likes	4,038.38	11,416.74	539	291,484	2,493.3	3,493.0	551	47,777
Δ Facebook Likes	151.29	1,884.58	0	271,910	77.59	423.74	0	32,441
Backers	813.80	1,678.78	1	15,998	213.67	796.21	1	10,944
Δ Backers	30.49	149.16	0	7,360	6.65	64.47	0	5092
Accum. funding	76,173.17	233,081.2	8	3,390,551	17,355.16	71,208.30	26	1,078,853
Funding goal	47,870.69	77,691.58	8	900,000	855,911.9	2.79e+07	500	1.00e+09

Figure 6 depicts the distribution of fraudulent behavior with respect to the campaign category. We immediately recognize the higher standard deviation for Indiegogo, where over 9% of campaigns in the category "Technology" showed unnatural peaks in the growth of Facebook Likes. However, it can be seen that, despite the higher standard deviation, the categories in which campaigns are most and least prone to receive fake Likes are distributed rather similarly between both platforms.

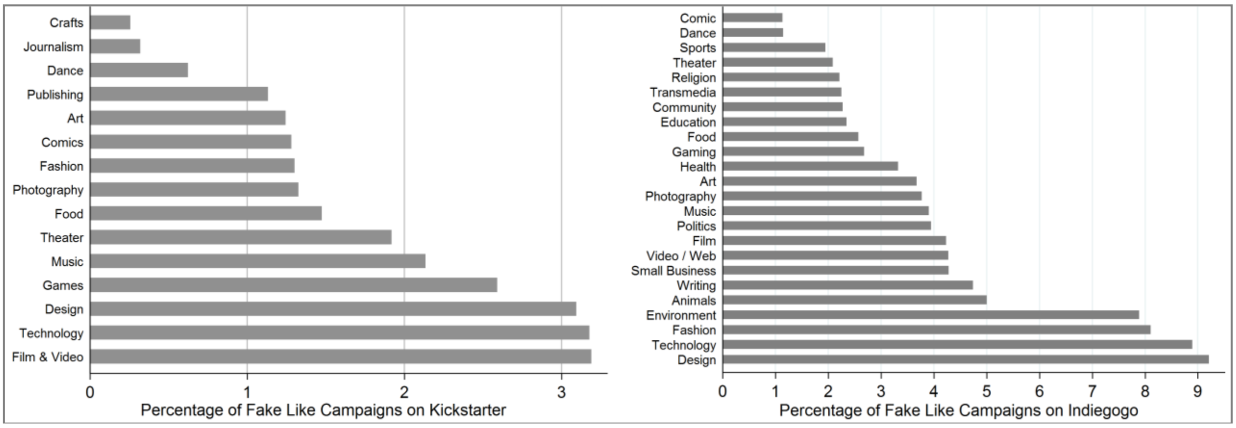


Figure 6: Percentage of Campaigns in the Distinct Categories on Indiegogo and Kickstarter that Received Non-genuine Facebook Likes During the Campaign Life Cycle

As we are using a panel dataset, we are able to identify the exact date a campaign received the non-genuine Facebook Likes. Figure 7 shows the growth of Facebook Likes for two separate campaigns from our dataset over the campaign life cycle and serves as an illustrative example for the distinct peak that can be observed when non-genuine Facebook Likes are acquired compared to a natural growth. We further use our data to plot the date of the acquisition against the accumulated funding the campaign eventually received by the end of the campaign life cycle (Figure 8). Each dot represents the exact point in time when the unnatural peak occurred. On the y-axis, we depicted the fraction of the total amount of the accumulated funding a campaign raised. We can see that the majority of creators try to increase the odds of success by making use of the artificial manipulation of Likes early in the campaign's life cycle, represented by the dense cluster in the lower left corner. Drawing from this representation, we can also see that most campaigns are above the reference line, indicating that their action hurt their funding progress. Many campaigns were even unable to attract any additional funding after the manipulation of Facebook Likes, as represented by the dots on the top end. Interestingly, we do not see any apparent differences between Kickstarter and Indiegogo in this graph.

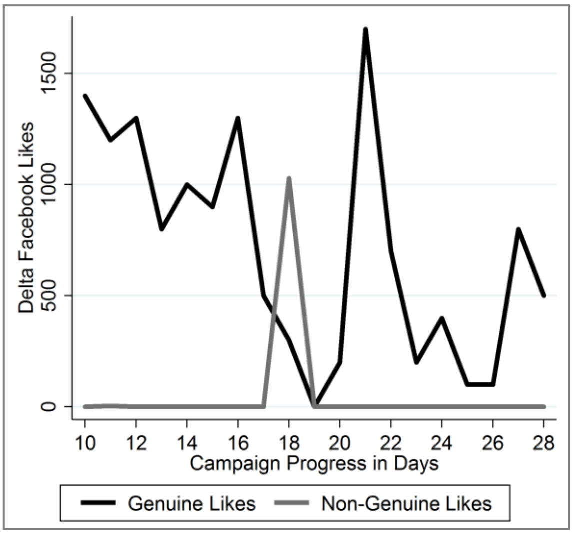


Figure 7: Example of Genuine and Non-genuine Peaks in Facebook Likes

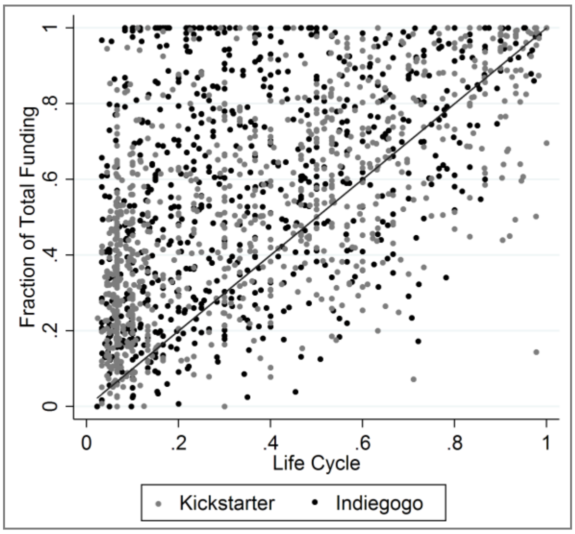


Figure 8: Timing of Unnatural Peaks with Respect to Funding and Life Cycle

4.4.2 Effects of Fake Facebook Likes on the Decision-Making of Backers

We now turn to our econometric evidence for the effect fake social information in the form of Facebook Likes has on the decision-making of prospective backers on Kickstarter and Indiegogo. We ran a total of four models for our econometric results as depicted in Table 8. The first two used our data of Kickstarter, while the latter two models describe the effects on Indiegogo. Specification 1-1 and 2-1 include a before/after dummy for the purchase of Fake Likes. In order to model the dynamic effects and to rule out other rival explanations, we create a set of ten dummies for the 5 days pre and post the artificial manipulation in the specifications 1-2 and 2-2. Observations in Model 1-2 and 2-2 are thus restricted to be within a 10 day time period from the purchase of Fake Likes.

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

Table 8: Results from Fixed Effects Negative Binominal Regression

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

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

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

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

In order to test whether any correlation exists between the characteristics of individual campaigns and the likelihood of any artificial manipulation of quality signals, we used a probit model with the occurrence of fake Facebook Likes as the binary dependent variable (Table 9). Though this does not allow us to interpret the coefficients directly, we are able to interpret whether the respective characteristics have a positive or negative effect on the likelihood of fake Facebook Likes. To assess the role of individual campaign quality, we mainly focused on the role of preparedness as a signal of quality to the prospective backers (Chen et al., 2009; Mollick, 2014). We thus selected variables from our dataset that reflect how well prepared and how involved in the community the creators of the campaigns were.

One of the key elements of every crowdfunding campaign on both platforms is the campaign video. A high quality video would, for example, make it more likely for potential backers to share the campaign via Facebook and could thus make it less attractive for the creators to acquire additional fake Facebook Likes. Surprisingly and an in contrast to Proposition 4, we see that if a video exists, the artificial manipulation of social information becomes more likely. The same is true for a number of other variables such as the number of updates a creator provides during the campaign life cycle (see Table 9).

Table 9: Results from the Probit Regression

Fake Likes (Dummy)	Kickstarter	Indiegogo
ln(funding goal)	0.2^{***} (13.78)	0.14^{***} (11.17)
Campaign duration	0.0065^{***} (3.67)	0.0056^{***} (3.66)
Number of rewards	0.016^{***} (6.60)	0.0051 (1.52)
Campaigns backed	0.0012 (1.76)	0.0023 (1.92)
Campaigns created	-0.026 (-1.24)	-0.024 (-0.97)
Video	0.28^{***} (3.57)	0.11^{*} (2.11)
ln(updates)	0.32^{***} (15.22)	0.52^{***} (27.28)
ln(Facebook friends)	0.18^{***} (8.50)	–
Team size	–	-0.006 (-0.71)
Concentration	1.2^{***} (3.47)	-0.088 (-0.25)
Crowdedness	0.12^{**} (2.98)	-0.0063 (-0.16)
Log Likelihood	-2,230	-2,243
Wald-Chi²	795	1123
Pseudo R²	0.2	0.22
Observations	30,159	20,152

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

Finally, we also proposed that, as the intensity of competition increases, creators will be less interested in following the market rules and more likely to acquire fake Likes. We thus measured the dynamic market crowdedness and concentration (Herfindahl–Hirschman Index) for every category on both platforms in order to determine the intensity of competition on each day. The results in Table 9 suggest that, on Kickstarter, an increased competition does in fact increase the likelihood of artificial manipulations of quality signals in the respective category, while there is no similar effect on Indiegogo.

4.5 Discussion and Implications

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

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

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

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

4.6 Limitations, Further Research, and Conclusion

Our study provides important insights for both research and practice. However, we acknowledge certain limitations that have to be considered when interpreting the results. First, as the dynamics of crowdfunding are different from those in a traditional e-commerce setting between a seller and a buyer, the applicability to this context might be limited. Second, we believe that the crowdfunding community is not truly representative for other electronic markets, as they can generally be characterized as very internet-savvy. We therefore suspect that the effects of non-genuine social information on the decision-making of a more representative sample might be different, but not necessarily weaker. Third, even though we used the two largest crowdfunding platforms, we limited the scope of our study to reward-based crowdfunding, which limits the generalizability of our results. Fourth, we were unable to compare the effects of different types of social information in this study, which would further increase the validity of the results. Fifth, we only considered the effects of the occurrence of fake Facebook Likes on the backers. However, one could imagine that fraudulent behavior by few campaign creators could reflect negatively on the rest of the community. Finally, we are aware that our algorithm to identify the acquisition of fake Likes could be an imperfect indicator and might classify very few campaigns as fraudulent even though they are not and vice versa. However, we expect the proportion of these wrongly classified campaigns to be negligible and they should thus not distort our results.

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

5 Signaling Personality Traits in Platform Ecosystems

Title:	Personality Matters: How Signaling Personality Traits can Influence the Adoption and Diffusion of Crowdfunding Campaigns (2016)
Authors:	Thies, Ferdinand Wessel, Michael Rudolph, Jan Benlian, Alexander
Published in:	Proceedings of the 24th European Conference on Information Systems (ECIS), Istanbul, Turkey

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.*

5.1 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 webpage 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, 2013; Loughran and McDonald, 2011). 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 (Allison et al., 2013; Herzenstein et al., 2011b; 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 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 persistency 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 (Bozionelos, 2004; Judge and Ilies, 2002; Costa et al., 1991; 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 market place and the diffusion in social media. Our research is guided by the following research questions:

> ***RQ 1:*** *How does signaling different personality traits on Kickstarter influence the funding decision of backers and ultimately the outcome of the respective crowdfunding campaign?*
>
> ***RQ 2:*** *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.

5.2 Theoretical Background and Prior Research

5.2.1 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 (Ciavarella et al., 2004; Stewart and Roth, 2001; Begley and Boyd, 1988). 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 (2015), 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 (FFM), 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 10: 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 10): 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 (McElroy et al., 2007; McCrae and Costa Jr, 1997; Judge and Ilies, 2002). 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 (McElroy et al., 2007; Barrick and Mount, 1991) 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 et al., 2001; Barrick and

Mount, 1991). 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 (McCrae and Costa Jr, 1999; Judge et al., 1999; Graziano and Eisenberg, 1997). 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.

5.2.2 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 webpage. 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 (Biswas and Biswas, 2004; Stiglitz, 1990). 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 (Connelly et al., 2011; Kirmani and Rao, 2000).

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; Moss et al., 2015; Allison et al., 2015; Ahlers 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 (Moon and Nass, 1996; Nass and Lee, 2001; Nass et al., 1995) and are subsequently affected in their decision-making (Al-Natour et al., 2006; Hess et al., 2009).

5.3 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[10]. 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 among their peers.

5.3.1 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 webpages, is an integral part of many crowdfunding campaigns. We therefore used the Web Speech API[11] 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

10 https://watson-pi-demo.mybluemix.net
11 https://dvcs.w3.org/hg/speech-api/raw-file/tip/speechapi.html

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 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.

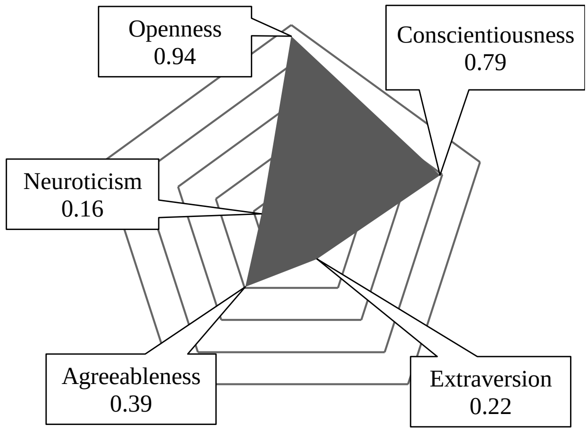
5.3.2 Measuring Personality Traits

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 artificial 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 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[12] and show an excerpt of the input as well as the calculated output by IBM's Personality Insights in Table 11. This text shows a high score in openness and conscientiousness, and low to medium values in neuroticism, extraversion, and agreeableness.

Table 11: Example Text and the Output by Personality Insights.

Input (N=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. […]"	

5.3.3 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 (Thies et al., 2014; Mollick, 2014). As we are interested in the effects of personality traits reflected in the project descriptions and videos, we use the op-

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

erationalized 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.

5.3.4 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 model:

$$\mathbf{Pr}(y=1|\mathbf{x}) = F(\mathbf{x}\boldsymbol{\beta})$$

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 formulization is, analogous to the above, as follows:

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

5.3.5 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.

5.4 Results

Descriptive statistics and the correlation matrix can be found in Table 12. 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 12 between the different personality traits are in line with former research and studies (e.g., van der Linden et al., 2010; Anusic et al., 2009) and are well below the threshold level to be of serious concern for the regression analysis. Table 13 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 for the 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 12: 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)	Goal in 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.		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		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)	Agreeable.		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		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.		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		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)	Agreeable.		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		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, 2015b). 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 base line models are therefore in line with prior research.

Table 13: 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 (control)	Included	Included	Included	Included	Included	Included	Included	Included
Category (control)	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.

5.5 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 (Hess et al., 2009; Moon and Nass, 1996; Nass et al., 1995; Nass and Lee, 2001). 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 (Allison et al., 2013; Herzenstein et al., 2011b; 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, 2013; Loughran and McDonald, 2011).

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 webpages 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.

5.6 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; Gosling et al., 2003; Judge and Ilies, 2002). 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 market place as well as the diffusion of crowdfunding campaigns in social media.

6 Relinquishing Control in Platform Ecosystems

Title:	The Effects of Relinquishing Control in Platform Ecosystems: Implications from a Policy Change on Kickstarter (2015)
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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*

6.1 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 (Mollick, 2014; Schwienbacher and Larralde, 2012). 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 indirect 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., Armstrong, 2006; Rochet and Tirole, 2003; 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; Boudreau, 2012; Tiwana et al., 2010). 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 (Kickstarter, 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 (Kelion, 2014; Jeffries, 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 for 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:

> ***RQ 1**: How does relinquishing input control affect the platform participants and their behavior?*
>
> ***RQ 2**: 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., Choudhury and Sabherwal, 2003; Kirsch et al., 2002). 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., Burtch et al., 2015; Claussen et al., 2013). 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.

6.2 Theoretical Background

6.2.1 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. Indirect 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 (Benlian et al., 2015; Ghazawneh and Henfridsson, 2013). 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 (Kirsch, 1997; Ouchi, 1979). 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., Eisenhardt, 1985; Ouchi, 1979). 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., Kirsch, 1996; Ouchi, 1979). 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 et al., 2002; Kirsch, 1997; 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; Wareham et al., 2014; Goldbach 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., Boudreau, 2010; Cardinal et al., 2004; Liu et al., 2014; Snell, 1992), prior IS research has mainly focused on output, process, and clan control, overlooking the increasing relevance of input control (e.g., Choudhury and Sabherwal, 2003; Kirsch et al., 2002).

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.

6.2.2 Crowdfunding

Crowdfunding, which builds on the broader concept of crowdsourcing (e.g., Bayus, 2013; Huang et al., 2014; Poetz and Schreier, 2012), 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 (Lin and Viswanathan, 2015; Agrawal et al., 2011), the project creator's social network (e.g., Agrawal et al., 2010; Lin et al., 2013a), 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.

6.3 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, 2015e). 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.

6.3.1 Economics of Reward-based Crowdfunding

6.3.1.1 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[13], 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 (AON) 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 (Burtch et al., 2013; Mollick, 2014; Shane and Cable, 2002). 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).

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

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 (Burtch et al., 2015; Mollick, 2014).

6.3.1.2 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 (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 (Connelly et al., 2011; Spence, 1973; Kirmani and Rao, 2000). 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, 2015a). 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 general 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[14] (Wikimedia Foundation, 2015).

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, 2015a). 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. 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 (Chevalier and Mayzlin, 2006; Duan et al., 2008), 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, 2015a).

6.3.2 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

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

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 (Kelion, 2014; Jeffries, 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 (Kickstarter, 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 (Kickstarter, 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."* (Kickstarter, 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.

6.4 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 (Claussen et al., 2013; Goldfarb and Tucker, 2011; Tucker and Zhang, 2011). 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 14 and Table 15. 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.

6.4.1 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 14, 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 platform revenue sharply increased, pointing towards less predictable revenue streams for the platform.

Table 14: 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	.11 (.32)	.12 (.32)	.11 (.32)	-8%
Video	Dummy is 1 if the campaign contains a video; 0 otherwise	.68 (.5)	.80 (.4)	.61 (.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	.07 (.25)	.07 (.25)	.06 (.24)	-3%
Update Frequency (UF)	Number of daily updates the creator posts	.14 (.28)	.18 (.34)	.11 (.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	.33 (.47)	.42 (.49)	.29 (.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 9 shows the average number of new campaigns on Kickstarter during our observational period. The underlying data for Figure 9 and Figure 10 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 9 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 9. 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.

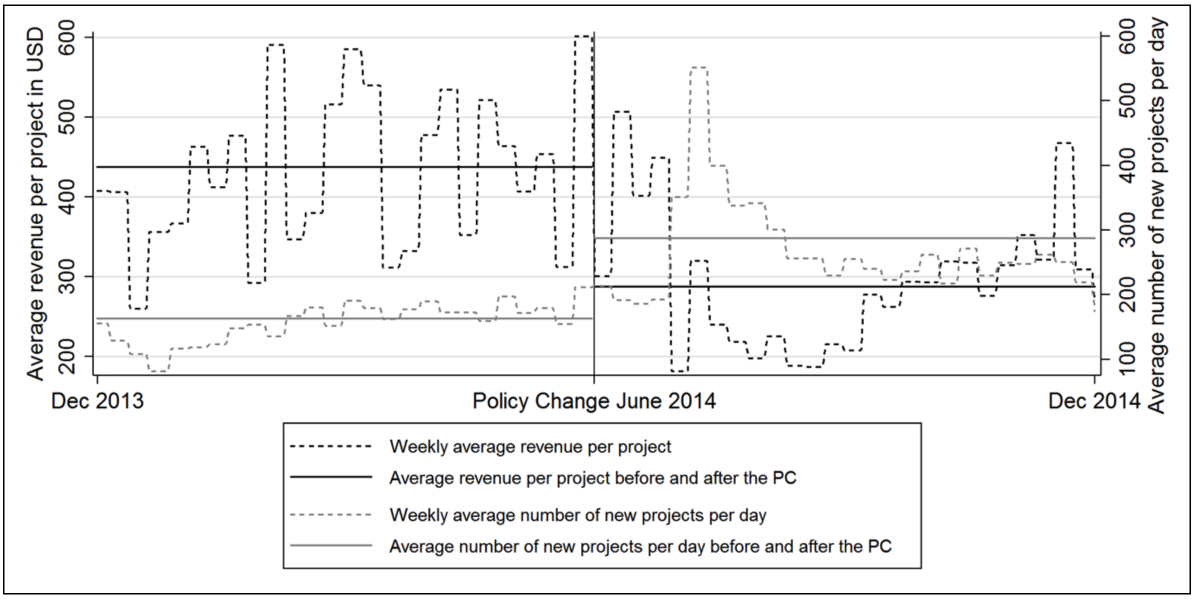


Figure 9: Effects of the Policy Change on Count and Revenue of Campaigns

Figure 10 combines the two graphs from Figure 9 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 *The Coolest Cooler* that started shortly after the policy change.

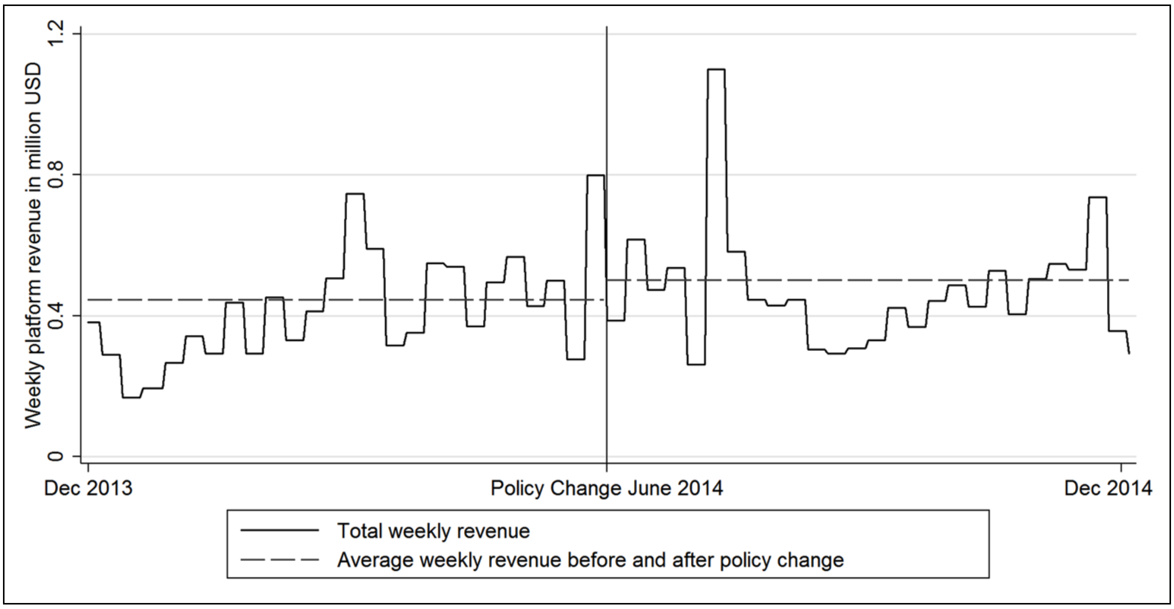


Figure 10: Effects of the Policy Change on Platform Revenue

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.

6.4.2 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, 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 (Cameron and Trivedi, 2005; Long, 1997) 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 15: Pairwise Correlations for Numerical Variables

		1	2	3	4	5	6	7	8	9	10	11
1	Backers	1										
2	Duration	.00	1									
3	LN (Pledge Goal)	.10*	.21*	1								
4	Staff Pick	.16*	-.03*	.11*	1							
5	Video	.08*	-.02*	.23*	.20*	1						
6	LN (Description Len.)	.13*	.01	.31*	.23*	.38*	1					
7	Spelling Errors	.01*	.02*	.05*	-.00	.01*	.012*	1				
8	Update Frequency	.22*	-.15*	.04*	.26*	.22*	.31*	.02*	1			
9	LN (Facebook Shares)	.20*	.00	.21*	.33*	.43*	.40*	-.00	.38*	1		
10	LN (Twitter Tweets)	.22*	.01*	.24*	.34*	.35*	.39*	.01*	.40*	.71*	1	
11	Policy Change (PC)	-.03*	.02*	-.05*	-.01	-.20*	-.15*	-.01	-.12*	-.09*	-.04*	1

Note: t statistics are omitted for brevity. * $p < .05$.

We included several controls in our model to account for alternative explanations. All numerical variables and their correlations are given in Table 15. 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 16: 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	-.00	-.00	-.00	-.00	-.00	-.00	-.00	-.00	-.00
LN (Pledge Goal)	-.01*	-.01*	-.01*	-.01*	-.01*	-.01*	-.01*	-.01*	-.01*
Staff Pick	.53***	.53***	.39***	.53***	.53***	.53***	.52***	.52***	.52***
Video	.35***	.34***	.34***	.19***	.34***	.34***	.34***	.32***	.33***
LN (Description Len.)	.14***	.14***	.14***	.14***	.1***	.14***	.14***	.13***	.14***
Spelling Errors	-.18***	-.18***	-.18***	-.18***	-.18***	-.17***	-.18***	-.18***	-.18***
Update Frequency	2.37***	2.34***	2.35***	2.35***	2.35***	2.34***	1.99***	2.35***	2.36***
LN (Facebook Shares)	.39***	.4***	.4***	.4***	.4***	.4***	.4***	.33***	.4***
LN (Twitter Tweets)	.16***	.16***	.16***	.16***	.16***	.16***	.16***	.16***	.11***
Policy Change (PC)		-.89***	-.92***	-1.06***	-1.33***	-.89***	-1***	-1.23***	-.99***
PC x Staff Pick			.22***						
PC x Video				.23***					
PC x LN (DL)					.06***				
PC x Spelling Errors						-.01			
PC x Update Freq.							.77***		
PC x LN (FBS)								.12***	
PC x LN (TTW)									.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 < .05, ** p < .01, *** p < .001.

Based on the results of model (2) in Table 16, 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 .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.

6.4.3 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.

6.5 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" (Kickstarter, 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, 2015d). 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.

6.5.1 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., Choudhury and Sabherwal, 2003; Kirsch et al., 2002). 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., Burtch et al., 2015; Claussen et al., 2013) 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.

6.5.2 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.

6.5.2.1 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; Boudreau, 2012; Tiwana, 2015; Tiwana et al., 2010). 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, 2015c).

6.5.2.2 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.

6.5.2.3 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.

6.6 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.

7 Conclusion and Contributions

Platform ecosystems are becoming a ubiquitous phenomenon in a world shaped by digitization and global reach. Here, crowdfunding has become an increasingly successful alternative for raising funds on a global scale, by leveraging several advantages of platform ecosystems. This thesis was motivated by the need to deepen our theoretical as well as practical understanding of the dynamics and mechanisms in such ecosystems, which have been gaining rapid traction in recent years. Hence, we chose the research context of crowdfunding to provide an isolated but still exemplary area for examining the actions of stakeholders and the subsequent effects on other members of the platform ecosystem. Against this background, four studies have been conducted in order to adequately represent the actions of the respective stakeholder group. The final parts of this thesis, therefore, summarize the main theoretical and practical contributions in chapter 7.1. and 7.2., respectively. Even though a very specific research context was chosen, results and contributions are not strictly limited to crowdfunding, as the mechanics and dynamics are applicable to other platform ecosystems as well.

7.1 Theoretical Contributions

Overall, the findings across the four articles contribute to IS, social media and entrepreneurship literature by enhancing our understanding of platform ecosystems in general and crowdfunding in particular, which is increasingly used by entrepreneurs for financing their start-ups. As the studies included in this thesis take different perspectives of stakeholders into account and draw on different literature streams, the main theoretical contributions with regard to each participant's actions will be presented separately.

Regarding the role of consumers in a platform ecosystem, we advanced our understanding of the dynamic interplay among social media, and consumer's actual behavior. The first article is among the first studies to provide evidence that popularity information and eWOM have to be considered together, as they dynamically influence each other. We discover strong Granger-causal interdependencies that highlight the reciprocal and intertwined nature of influence among eWOM and popularity information over time. Future studies should therefore examine these social interaction mechanisms in combination rather than in isolation. Furthermore, we show that popularity information has a more immediate effect on consumer's decision-making, but attenuates rather quickly. On the other hand, eWOM requires a longer build-up time but its effectiveness persists for a longer period. We therefore expand previous IS and social media research by extending the former one-directional relationships of eWOM and popularity information. We do so by fully accounting for the time-varying dynamic effects in a system of mutually interdependent endogenous variables (Luo et al., 2013). The study also serves different calls for research to further investigate the evolution and interrelationships of multiple time series across information systems and platforms in an increasingly interconnected IT world (Adomavicius et al., 2012; Tiwana et al., 2010).

For the actions of the producers or creators that were closely examined in articles 2 and 3, our main theoretical contributions are twofold. First, to the best of our knowledge, article 2 is one of the first studies focused on the effects of fake social information on consumer decision-making. Here, we were able to show that despite the low information content, quantitative social information can have a substantial effect on consumer decision-making, and demonstrated how it evolves over time. Hence, we contribute to social media research by advancing our understanding of artificial manipulations of social information (Luca and Zervas, 2016).

In article 3 we then show that seemingly implicit characteristics of the creators in the form of personality traits influence the decision-making of customers. Hence, we complement IS and human-computer interaction literature, which proved individuals are able to perceive personality cues from different types of media, including text and voice (Hess et al., 2009; Moon and Nass, 1996; Nass et al., 1995; Nass and Lee, 2001). Furthermore, prior IS research was mainly concerned with the effects of different personality traits of individuals on their own decision-making (e.g., McElroy et al., 2007; Devaraj et al., 2008). On a wider scope, the study also enriches prior research on the Big Five personality traits and computer-aided text analysis in general (e.g., Short et al., 2010).

The last study took the perspective of the platform provider, where we contribute to the IS control literature and to the emerging research on platform ecosystems. Previous IS control research neglected input control mechanisms and focused on output, process and clan control. (e.g., Choudhury and Sabherwal, 2003; Kirsch et al., 2002). Thus, ours is one of the first studies to conceptualize and examine input control as a formal control mechanism. Hence, we complement previous IS control studies and empirically demonstrate that a change in the input control mechanism can have tremendous financial and behavioral effects on platforms.

Taking a more abstract perspective, this dissertation enhances our understanding of the dynamics and mechanisms that are at work in a complex and evolving platform ecosystem. Furthermore, we provided compelling empirical evidence for our theoretical contributions. Still, we hope that these findings will be tested in other settings to spark the academic discourse about platform ecosystems and the viability of crowdfunding as a sustainable way to finance new businesses.

7.2 Practical Contributions

In addition to the theoretical contributions, there are a number of practical recommendations to be deducted from the studies. Again, we will separate the contributions for each stakeholder of the platform and focus on the research context of crowdfunding.

The first article is especially relevant for project creators. We showed that prospective backers are responsive to changes in popularity information, which has comparatively stronger and more immediate effects than eWOM, meaning that early support is likely to increase the chances of success further down the road of the campaign. Also, due to its persistent effect, eWOM should be a priority throughout the whole campaign lifecycle, as backers often learn about campaigns via their online social network. Project creators should therefore use social media marketing, encourage backers to share the campaign, comment on it on the platform and keep an active discussion with prospective and past backers.

In article 2, we showed that even though it appears attractive for creators to manipulate their quantitative social information, acquiring non-genuine Facebook Likes will not attract any additional backers for the project. With regard to platform providers, our results provide important evidence on the extent of manipulation as well as under what market conditions and campaign characteristics it is most prevalent.

From a practical perspective, article 3 provides valuable information for project creators and producers in a platform market in general. As consumers perceive personality traits via texts and videos, project creators should try to signal favorable aspects such as openness and agreeableness while avoiding signs of neuroticism in their campaign description and video. This could enhance adoption among backers as well as diffusion in social media.

The practical contributions of the fourth article are threefold. First, for the providers of platform ecosystems, it is crucial to develop a deep understanding of the complementor's goals, strategies and capabilities, as the effects of a policy change in platform governance are extremely difficult to predict and can have a profound impact on the ecosystem. Second, for the project creators, a relaxed input control to the platform seems attractive. Still, easier entrance goes along with stronger competition due to the rising number of rival campaigns, the stronger focus on the quality of individual campaigns and on the ability of the project creators to generate awareness for their campaigns. Third, for prospective backers decreased input control results in more projects, and consequently more available investment options. On the other hand, this also increases their search costs and possibly information asymmetries, as being able to publish a campaign on Kickstarter is not a credible quality anymore (Bakos, 1997).

In conclusion, this thesis provides a further step towards understanding the dynamic nature of platform ecosystems. In a nutshell, crowdfunding is an exemplary and transparent platform ecosystem. Here, consumers follow each other's actions and opinions, while supporting producers partly based on their personality, even though they sometimes cheat. Ultimately, this highly dynamic ecosystem is governed by a provider that can alter the rules of the game whenever he wishes.

We hope that our results provide impetus for further analysis of the interdependencies between the stakeholders of platform ecosystems, and could provide actionable recommendations to platform providers, project creators and project backers in the crowdfunding context.

References

Adler, C. (2011). "How Kickstarter Became a Lab for Daring Prototypes and Ingenious Products." Retrieved 2016-06-05 from http://www.wired.com/2011/03/ff_kickstarter/all/1

Adomavicius, G., Bockstedt, J. and Gupta, A. (2012), "Modeling supply-side dynamics of IT components, products, and infrastructure: An empirical analysis using vector autoregression", *Information Systems Research,* Vol. 23 No. 2, pp. 397-417.

Aggarwal, C. C. (2013), *Outlier Analysis,* Springer, New York.

Aghion, P. and Tirole, J. (1997), "Formal and real authority in organizations", *Journal of Political Economy,* Vol. 105 No. 1, pp. 1-29.

Agrawal, A., Catalini, C. and Goldfarb, A. (2010), "Entrepreneurial finance and the flat-world hypothesis: evidence from crowd-funding entrepreneurs in the arts".

Agrawal, A., Catalini, C. and Goldfarb, A. (2011), "The Geography of Crowdfunding", *National Bureau of Economic Research Working Paper Series,* Vol. No. 16820.

Agrawal, A., Catalini, C. and Goldfarb, A. (2014), "Some Simple Economics of Crowdfunding", *Innovation Policy and the Economy,* Vol. 14 No. 1, pp. 63-97.

Agrawal, A., Catalini, C. and Goldfarb, A. (2015), "Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions", *Journal of Economics & Management Strategy,* Vol. 24 No. 2, pp. 253-274.

Ahlers, G. K. C., Cumming, D., Günther, C. and Schweizer, D. (2015), "Signaling in Equity Crowdfunding", *Entrepreneurship Theory and Practice,* Vol. 39 No. 4, pp. 955–980.

Akerlof, G. A. (1970), "The market for 'lemons': Quality uncertainty and the market mechanism", *The Quarterly Journal of Economics,* Vol. 84 No. 3, pp. 488-500.

Al-Natour, S., Benbasat, I. and Cenfetelli, R. T. (2006), "The Role of Design Characteristics in Shaping Perceptions of Similarity: The Case of Online Shopping Assistants", *Journal of the Association for Information Systems,* Vol. 7 No. 12, pp. 821-861.

Allison, P. D. and Waterman, R. P. (2002), "Fixed-effects negative binomial regression models", *Sociological Methodology 2002, Vol 32,* Vol. 32, pp. 247-265.

Allison, T. H., Davis, B. C., Short, J. C. and Webb, J. W. (2015), "Crowdfunding in a Prosocial Microlending Environment: Examining the Role of Intrinsic Versus Extrinsic Cues", *Entrepreneurship Theory and Practice,* Vol. 39 No. 1, pp. 53-73.

Allison, T. H., McKenny, A. F. and Short, J. C. (2013), "The effect of entrepreneurial rhetoric on microlending investment: an examination of the warm-glow effect", *Journal of Business Venturing,* Vol. 28 No. 6, pp. 690-707.

Anderson, C. (2006), *The Long Tail: Why the Future of Business Is Selling Less of More,* Hyperion Books, New York City.

Andreoni, J. (2006), "Philanthropy", in Serge-Christophe, K. and Jean Mercier, Y. (Eds.) *Handbook of the Economics of Giving, Altruism and Reciprocity*, Elsevier, pp. 1201-1269.

Andrews, D. W. K. and Lu, B. (2001), "Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models", *Journal of Econometrics,* Vol. 101 No. 1, pp. 123-164.

Anusic, I., Schimmack, U., Pinkus, R. T. and Lockwood, P. (2009), "The Nature and Structure of Correlations Among Big Five Ratings: The Halo-Alpha-Beta Model", *Journal of Personality and Social Psychology,* Vol. 97 No. 6, pp. 1142–1156.

Arellano, M. and Bover, O. (1995), "Another Look at the Instrumental Variable Estimation of Error-Components Models", *Journal of Econometrics,* Vol. 68 No. 1, pp. 29-51.

Armstrong, M. (2006), "Competition in Two-Sided Markets", *RAND Journal of Economics,* Vol. 37 No. 3, pp. 668-691.

Arndt, J. (1967), "Role of Product-Related Conversations in the Diffusion of a New Product", *Journal of Marketing Research (JMR),* Vol. 4 No. 3, pp. 291-295.

Arthur, C. (2013). "How low-paid workers at 'click farms' create appearance of online popularity." Retrieved 2014-10-15 from http://www.theguardian.com/technology/2013/aug/02/click-farms-appearance-online-popularity

Baddeley, M. (2010), "Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses", *Philosophical Transactions of the Royal Society of London B: Biological Sciences,* Vol. 365 No. 1538, pp. 281-290.

Bakos, Y. (1997), "Reducing buyer search costs: Implications for electronic marketplaces", *Management Science,* Vol. 43 No. 12, pp. 1676-1692.

Bakos, Y. and Katsamakas, E. (2004), "Design and ownership of two-sided networks: implications for Internet intermediaries", *Journal of Management Information Systems,* Vol. 25 No. 2, pp. 171-202.

Baldwin, C. Y. and Woodard, C. J. (2009), "The Architecture of Platforms: A Unified View", in Gawer, A. (Ed.) *Platforms, Markets and Innovation*, Edward Elgar Publishing, Cheltenham, UK and Northampton, Massachusetts, pp. 19-44.

Barrick, M. R. and Mount, M. K. (1991), "The Big Five Personality Dimensions and Job Performance: A Meta-Analysis", *Personnel Psychology,* Vol. 44 No. 1, pp. 1-26.

Barrick, M. R., Mount, M. K. and Judge, T. A. (2001), "Personality and Performance at the Beginning of the New Millennium: What Do We Know and Where Do We Go Next?", *International Journal of Selection and Assessment,* Vol. 9 No. 1-2, pp. 9-30.

Batra, R. and Ray, M. L. (1986), "Affective responses mediating acceptance of advertising", *Journal of Consumer Research,* Vol. 13 No. 2, pp. 234-249.

Bayus, B. L. (2013), "Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community", *Management Science,* Vol. 59 No. 1, pp. 226-244.

Beaulieu, T., Sarker, S. and Sarker, S. (2015), "A Conceptual Framework for Understanding Crowdfunding", *Communications of the Association for Information Systems,* Vol. 37 No. 1, pp. 1-31.

Becker, G. S. (1991), "A note on restaurant pricing and other examples of social influences on price", *Journal of Political Economy,* Vol. 99 No. 5, pp. 1109-1116.

Begley, T. M. and Boyd, D. P. (1988), "Psychological characteristics associated with performence in entrepreneurial firms and smaller businesses", *Journal of Business Venturing,* Vol. 2 No. 1, pp. 79-93.

Belleflamme, P., Lambert, T. and Schwienbacher, A. (2014), "Crowdfunding: Tapping the right crowd", *Journal of Business Venturing,* Vol. 29 No. 5, pp. 585–609.

Benlian, A. and Hess, T. (2011), "The Signaling Role of IT Features in Influencing Trust and Participation in Online Communities", *International Journal of Electronic Commerce,* Vol. 15 No. 4, pp. 7-56.

Benlian, A., Hilkert, D. and Hess, T. (2015), "How Open Is This Platform? The Meaning and Measurement of Platform Openness From the Complementors' Perspective", *Journal of Information Technology,* Vol. 30 No. 3, pp. 209-228.

Berger, J. and Milkman, K. L. (2012), "What Makes Online Content Viral?", *Journal of Marketing Research,* Vol. 49 No. 2, pp. 192-205.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992), "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades", *Journal of Political Economy,* Vol. 100 No. 5, pp. 992-1026.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1998), "Learning from the Behavior of Others: Conformity, Fads and Informational Cascades", *The Journal of Economic Perspectives,* Vol. 12 No. 3, pp. 151-170.

Biswas, D. and Biswas, A. (2004), "The diagnostic role of signals in the context of perceived risks in online shopping: Do signals matter more on the Web?", *Journal of Interactive Marketing,* Vol. 18 No. 3, pp. 30-45.

Bloch, P. H., Sherrell, D. L. and Ridgway, N. M. (1986), "Consumer Search: An Extended Framework", *Journal of Consumer Research,* Vol. 13 No. 1, pp. 119-126.

Boudreau, K. J. (2010), "Open Platform Strategies and Innovation: Granting Access vs. Devolving Control", *Management Science,* Vol. 56 No. 10, pp. 1849-1872.

Boudreau, K. J. (2012), "Let a Thousand Flowers Bloom? An Early Look at Large Numbers of Software App Developers and Patterns of Innovation", *Organization Science,* Vol. 23 No. 5, pp. 1409-1427.

Bozionelos, N. (2004), "The big five of personality and work involvement", *Journal of Managerial Psychology,* Vol. 19 No. 1, pp. 69-81.

Branco, F. and Villas-Boas, J. M. (2012), "Competitive vices", Working paper.

Bresnahan, T. and Greenstein, S. (2014), "Mobile Computing: The Next Platform Rivalry", *American Economic Review,* Vol. 104 No. 5, pp. 475-80.

Briggs, S. R. (1992), "Assessing the Five Factor Model of Personality Description", *Journal of Personality,* Vol. 60 No. 2, pp. 253-293.

Brown, J., Broderick, A. J. and Lee, N. (2007), "Word of mouth communication within online communities: Conceptualizing the online social network", *Journal of Interactive Marketing,* Vol. 21 No. 3, pp. 2-20.

Built With (2014). "Facebook Like Usage Statistics." Retrieved 2014-11-02 from http://trends.builtwith.com/widgets/Facebook-Like

Burtch, G., Ghose, A. and Wattal, S. (2013), "An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets", *Information Systems Research,* Vol. 24 No. 3, pp. 499-519.

Burtch, G., Ghose, A. and Wattal, S. (2015), "The Hidden Cost of Accommodating Crowdfunder Privacy Preferences: A Randomized Field Experiment", *Management Science*.

Buttle, F. A. (1998), "Word of mouth: understanding and managing referral marketing", *Journal of Strategic Marketing,* Vol. 6 No. 3, pp. 241-254.

Cameron, A. C. and Trivedi, P. K. (2005), *Microeconometrics: Methods and Applications,* Cambridge University Press.

Cameron, A. C. and Trivedi, P. K. (2013), *Regression Analysis of Count Data,* Cambridge University Press.

Cardinal, L. B. (2001), "Technological Innovation in the Pharmaceutical Industry: The Use of Organizational Control in Managing Research and Development", *Organization Science,* Vol. 12 No. 1, pp. 19-36.

Cardinal, L. B., Sitkin, S. B. and Long, C. P. (2004), "Balancing and rebalancing in the creation and evolution of organizational control", *Organization Science,* Vol. 15 No. 4, pp. 411-431.

Cardon, M. S., Sudek, R. and Mitteness, C. (2009), "The impact of perceived entrepreneurial passion on angel investing", *Frontiers of Entrepreneurship Research,* Vol. 29 No. 2, p. 1.

Chellappa, R. K., Sambamurthy, V. and Saraf, N. (2010), "Competing in Crowded Markets: Multimarket Contact and the Nature of Competition in the Enterprise Systems Software Industry", *Information Systems Research,* Vol. 21 No. 3, pp. 614-630.

Chen, H., De, P. and Hu, Y. J. (2015), "IT-Enabled Broadcasting in Social Media: An Empirical Study of Artists' Activities and Music Sales", *Information Systems Research,* Vol. 26 No. 3, pp. 513-531.

Chen, X.-P., Yao, X. and Kotha, S. (2009), "Entrepreneur passion and preparedness in business plan presentations: a persuasion analysis of venture capitalists' funding decisions", *Academy of Management Journal,* Vol. 52 No. 1, pp. 199-214.

Chen, Y., Wang, Q. and Xie, J. (2011), "Online Social Interactions: A Natural Experiment on Word of Mouth versus Observational Learning", *Journal of Marketing Research,* Vol. 48 No. 2, pp. 238-254.

Cheung, C. M. K. and Thadani, D. R. (2012), "The impact of electronic word-of-mouth communication: A literature analysis and integrative model", *Decision Support Systems,* Vol. 54 No. 1, pp. 461-470.

Cheung, C. M. K., Xiao, B. S. and Liu, I. L. B. (2014), "Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions", *Decision Support Systems,* Vol. 65, pp. 50-58.

Chevalier, J. A. and Mayzlin, D. (2006), "The effect of word of mouth on sales: Online book reviews", *Journal of Marketing Research,* Vol. 43 No. 3, pp. 345-354.

Choudary, S. P. (2015), *Platform Scale: How an emerging business model helps startups build large empires with minimum investment,* Platform Thinking Labs.

Choudhury, V. and Sabherwal, R. (2003), "Portfolios of control in outsourced software development projects", *Information Systems Research,* Vol. 14 No. 3, pp. 291-314.

Cialdini, R. B. (2009), *Influence: Science and Practice,* Pearson Education, Boston.

Ciavarella, M. A., Buchholtz, A. K., Riordan, C. M., Gatewood, R. D. and Stokes, G. S. (2004), "The Big Five and venture survival: Is there a linkage?", *Journal of Business Venturing,* Vol. 19 No. 4, pp. 465-483.

Claussen, J., Kretschmer, T. and Mayrhofer, P. (2013), "The Effects of Rewarding User Engagement: The Case of Facebook Apps", *Information Systems Research,* Vol. 24 No. 1, pp. 186-200.

Connelly, B. L., Certo, S. T., Ireland, R. D. and Reutzel, C. R. (2011), "Signaling Theory: A Review and Assessment", *Journal of Management,* Vol. 37 No. 1, pp. 39-67.

Costa Jr, P. T. and McCrae, R. R. (1995), "Domains and Facets: Hierarchical Personality Assessment Using the Revised NEO Personality Inventory", *Journal of Personality Assessment,* Vol. 64 No. 1, pp. 21-50.

Costa, P. T., McCrae, R. R. and Dye, D. A. (1991), "Facet Scales for Agreeableness and Conscientiousness: A Revision of the NEO Personality Inventory", *Personality and Individual Differences,* Vol. 12 No. 9, pp. 887-898.

Coughlan, P. J. (2004), "The Golden Age of Home Video Games: from the reign of Atari to the rise of Nintendo", *Harvard Business School Case Study 9-704,* Vol. 487.

Cusumano, M. A. (2010), "Technology Strategy and Management Platforms and Services: Understanding the Resurgence of Apple", *Communications of the ACM,* Vol. 53 No. 10, pp. 22-24.

Cusumano, M. A. and Gawer, A. (2002), "The elements of platform leadership", *MIT Sloan Management Review,* Vol. 43 No. 3, pp. 51-60.

Daily, C. M., Certo, S. T. and Dalton, D. R. (2005), "Investment bankers and IPO pricing: does prospectus information matter?", *Journal of Business Venturing,* Vol. 20 No. 1, pp. 93-111.

Davis, A. and Khazanchi, D. (2008), "An empirical study of online word of mouth as a predictor for multi-product category e-commerce sales", *Electronic Markets,* Vol. 18 No. 2, pp. 130-141.

de Montjoye, Y.-A., Quoidbach, J., Robic, F. and Pentland, A. S. (2013), "Predicting Personality Using Novel Mobile Phone-Based Metrics", in Greenberg, A. M., Kennedy, W. G. and

Bos, N. D. (Eds.) *Social Computing, Behavioral-Cultural Modeling and Prediction*, Springer, pp. 48-55.

de Reuver, M. and Bouwman, H. (2012), "Governance mechanisms for mobile service innovation in value networks", *Journal of Business Research,* Vol. 65 No. 3, pp. 347-354.

Dekimpe, M. G. and Hanssens, D. M. (1995), "The persistence of marketing effects on sales", *Marketing Science,* Vol. 14 No. 1, pp. 1-21.

Dellarocas, C. (2003), "The digitization of word of mouth: Promise and challenges of online feedback mechanisms", *Management science,* Vol. 49 No. 10, pp. 1407-1424.

Dellarocas, C., Gao, G. and Narayan, R. (2010), "Are consumers more likely to contribute online reviews for hit or niche products?", *Journal of Management Information Systems,* Vol. 27 No. 2, pp. 127-158.

Devaraj, S., Easley, R. F. and Crant, J. M. (2008), "How Does Personality Matter? Relating the Five-Factor Model to Technology Acceptance and Use", *Information Systems Research,* Vol. 19 No. 1, pp. 93-105.

Dewan, S. and Ramaprasad, J. (2014), "Social Media, Traditional Media, and Music Sales", *MIS Quarterly,* Vol. 38 No. 1, pp. 101-121.

Duan, W., Gu, B. and Whinston, A. B. (2008), "The Dynamics of Online Word-of-Mouth and Product Sales – An Empirical Investigation of the Movie Industry", *Journal of Retailing,* Vol. 84 No. 2, pp. 233-242.

Duan, W., Gu, B. and Whinston, A. B. (2009), "Informational Cascades And Software Adoption On The Internet: An Empirical Investigation", *MIS Quarterly,* Vol. 33 No. 1, pp. 23-48.

Eisenhardt, K. M. (1985), "Control: Organizational and economic approaches", *Management Science,* Vol. 31 No. 2, pp. 134-149.

Eisenmann, T., Parker, G. and Van Alstyne, M. W. (2006), "Strategies for Two-Sided Markets", *Harvard Business Review,* Vol. 84 No. 10.

Elberse, A. (2008), "Should You Invest in the Long Tail?", *Harvard Business Review,* Vol. 86 No. 7/8, p. 88.

Engel, J. F. and Blackwell, R. D. (1982), *Consumer Behavior,* The Dryden Press, Chicago.

Evans, D. S. and Schmalensee, R. (2016), *Matchmakers: The New Economics of Multisided Platforms,* Harvard Business Review Press.

Evans, D. S., Schmalensee, R., Noel, M. D., Chang, H. H. and Garcia-Swartz, D. D. (2011), "Platform economics: Essays on multi-sided businesses", *PLATFORM ECONOMICS: ESSAYS ON MULTI-SIDED BUSINESSES, David S. Evans, ed., Competition Policy International*.

Facebook, Inc. (2015). "What are fake Page likes?" Retrieved 2016-06-05 from https://www.facebook.com/help/1540525152857028

Facebook Inc. (2014). "What does it mean to "Like" something?" Retrieved 2014-10-12 from https://www.facebook.com/help/110920455663362

Facebook Inc. (2015a). "What are fake Page likes?" Retrieved 2015-03-15 from https://www.facebook.com/help/1540525152857028

Facebook Inc. (2015b). "Why shouldn't I buy fake Page likes?" Retrieved 2015-03-15 from https://www.facebook.com/help/241847306001585

Fang, Z., Luo, X. and Jiang, M. (2013), "Quantifying the Dynamic Effects of Service Recovery on Customer Satisfaction Evidence From Chinese Mobile Phone Markets", *Journal of Service Research,* Vol. 16 No. 3, pp. 341-355.

Fast, L. A. and Funder, D. C. (2008), "Personality as Manifest in Word Use: Correlations With Self-Report, Acquaintance Report, and Behavior", *Journal of Personality and Social Psychology,* Vol. 94 No. 2, pp. 334–346.

Federal Trade Commission (2009), "Guides Concerning the Use of Endorsements and Testimonials in Advertising", in Commission, F. T. (Ed. *16 CFR Part 255*.

Finney, D. J. (1971), *Probit Analysis,* Cambridge University Press, New York.

Forman, C., Ghose, A. and Wiesenfeld, B. (2008), "Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets", *Information Systems Research,* Vol. 19 No. 3, pp. 291-313.

Galak, J., Small, D. and Stephen, A. T. (2011), "Microfinance Decision Making: A Field Study of Prosocial Lending", *Journal of Marketing Research,* Vol. 48 No. Special Issue, pp. 130-137.

Galuba, W., Aberer, K., Chakraborty, D., Despotovic, Z. and Kellerer, W. (2010), "Outtweeting the twitterers-predicting information cascades in microblogs", in *Proceedings of the 3rd Conference on Online Social Networks*, Boston, MA, pp. 1-9.

Gara, T. (2013). "One Big Doubt Hanging Over Twitter's IPO: Fake Accounts." Retrieved 2014-11-05 from http://online.wsj.com/articles/SB10001424052702303492504579113754194762812

Ghazawneh, A. and Henfridsson, O. (2013), "Balancing platform control and external contribution in third-party development: the boundary resources model", *Information Systems Journal,* Vol. 23 No. 2, pp. 173-192.

Godes, D. and Mayzlin, D. (2004), "Using online conversations to study word-of-mouth communication", *Marketing science,* Vol. 23 No. 4, pp. 545-560.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M. and Verlegh, P. (2005), "The Firm's Management of Social Interactions", *Marketing Letters,* Vol. 16 No. 3-4, pp. 415-428.

Goldbach, T., Kemper, V. and Benlian, A. (2014), "Mobile Application Quality and Platform Stickiness under Formal vs. Self-Control — Evidence from an Experimental Study", *International Conference on Information Systems (ICIS)*, Auckland, New Zealand.

Goldberg, L. R. (1990), "An Alternative 'Description of Personality': The Big-Five Factor Structure", *Journal of Personality and Social Psychology,* Vol. 59 No. 6, pp. 1216-1229.

Goldfarb, A. and Tucker, C. E. (2011), "Privacy Regulation and Online Advertising", *Management Science,* Vol. 57 No. 1, pp. 57-71.

Gorman, M. and Sahlman, W. A. (1989), "What do venture capitalists do?", *Journal of Business Venturing,* Vol. 4 No. 4, pp. 231-248.

Gosling, S. D., Rentfrow, P. J. and Swann, W. B. (2003), "A very brief measure of the Big-Five personality domains", *Journal of Research in Personality,* Vol. 37 No. 6, pp. 504-528.

Goswami, S., Teo, H. H. and Chan, H. C. (2009), "Decision-Maker Mindfulness in IT Adoption: The Role of Informed Culture and Individual Personality", *International Conference on Information Systems (ICIS 2009)*, Phoenix.

Granger, C. W. J. (1969), "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods", *Econometrica,* Vol. 37 No. 3, pp. 424-438.

Graziano, W. and Eisenberg, N. (1997), "Agreeableness: A dimension of Personality", in Hogan, R., Johnson, J. and Briggs, S. (Eds.) *Handbook of Personality Psychology*, Academic Press, San Diego, pp. 795-824.

Greene, W. (2008), "Functional forms for the negative binomial model for count data", *Economics Letters,* Vol. 99 No. 3, pp. 585-590.

Gulati, R., Puranam, P. and Tushman, M. (2012), "Meta-organization design: Rethinking design in interorganizational and community contexts", *Strategic Management Journal,* Vol. 33 No. 6, pp. 571-586.

Hagiu, A. (2011), *Quantity Vs. Quality: Exclusion by Platforms with Networks Effects*.

Hansen, M. T. and Haas, M. R. (2001), "Competing for attention in knowledge markets: Electronic document dissemination in a management consulting company", *Administrative Science Quarterly,* Vol. 46 No. 1, pp. 1-28.

Hausman, J. A. and Taylor, W. E. (1981), "Panel Data and Unobservable Individual Effects", *Econometrica,* Vol. 49 No. 6, pp. 1377-1398.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G. and Gremler, D. D. (2004), "Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet?", *Journal of Interactive Marketing,* Vol. 18 No. 1, pp. 38-52.

Herzenstein, M., Dholakia, U. M. and Andrews, R. L. (2011a), "Strategic Herding Behavior in Peer-to-Peer Loan Auctions", *Journal of Interactive Marketing,* Vol. 25 No. 1, pp. 27-36.

Herzenstein, M., Sonenshein, S. and Dholakia, U. M. (2011b), "Tell Me a Good Story and I May Lend You Money: The Role of Narratives in Peer-to-Peer Lending Decisions", *Journal of Marketing Research,* Vol. 48 No. Special Issue, pp. 138-149.

Hess, T. J., Fuller, M. and Campbell, D. E. (2009), "Designing Interfaces with Social Presence: Using Vividness and Extraversion to Create Social Recommendation Agents", *Journal of the Association for Information Systems,* Vol. 10 No. 12, pp. 889-919.

Hirschman, A. O. (1964), "The Paternity of an Index", *American Economic Review,* Vol. 54 No. 5, pp. 761-762.

Holtz-Eakin, D., Newey, W. and Rosen, H. S. (1988), "Estimating Vector Autoregressions with Panel Data", *Econometrica,* Vol. 56 No. 6, pp. 1371-1398.

Howe, J. (2008), *Crowdsourcing: Why the Power of the Crowd Is Driving the Future of Business,* Crown Publishing Group.

Huang, Y., Singh, P. V. and Srinivasan, K. (2014), "Crowdsourcing New Product Ideas Under Consumer Learning", *Management Science,* Vol. 60 No. 9, pp. 2138-2159.

Huck, S. and Oechssler, J. (2000), "Informational cascades in the laboratory: Do they occur for the right reasons?", *Journal of Economic Psychology,* Vol. 21 No. 6, pp. 661-671.

Hui, J. S., Greenberg, M. D. and Gerber, E. M. (2014), "Understanding the role of community in crowdfunding work", *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, Baltimore, Maryland, USA, ACM pp. 62-74.

IBM Watson Developer Cloud (2015). "The science behind the Personality Insights service." Retrieved 2014-11-20 from https://www.ibm.com/smarterplanet/us/en/ibmwatson/developercloud/doc/personality-insights/science.shtml

Jabr, W. and Zheng, Z. (2014), "Know Yourself and Know Your Enemy: An Analysis of Firm Recommendations and Consumer Reviews in a Competitive Environment", *MIS Quarterly,* Vol. 38 No. 3, pp. 635-654.

Jahng, J. J., Jain, H. and Ramamurthy, K. (2002), "Personality traits and effectiveness of presentation of product information in e-business systems", *European Journal of Information Systems,* Vol. 11 No. 3, pp. 181-195.

Jeffries, A. (2014). "Kickstarter's next campaign: The original crowdfunder is loosening its rules and opening the floodgates." Retrieved 2015-03-01 from http://www.theverge.com/2014/6/3/5775548/kickstarter-s-next-campaign

Jensen, M. L., Averbeck, J. M., Zhang, Z. and Wright, K. B. (2013), "Credibility of anonymous online product reviews: A language expectancy perspective", *Journal of Management Information Systems,* Vol. 30 No. 1, pp. 293-324.

Jindal, N., Liu, B. and Lim, E.-P. (2010), "Finding unusual review patterns using unexpected rules", in *Proceedings of the 19th ACM International Conference on Information and Knowledge Management*, pp. 1549-1552.

Judge, T. A., Higgins, C. A., Thoresen, C. J. and Barrick, M. R. (1999), "The Big Five Personality Traits, General Mental Ability, and Career Success Across the Life Span", *Personnel Psychology,* Vol. 52 No. 3, pp. 621-652.

Judge, T. A. and Ilies, R. (2002), "Relationship of Personality to Performance Motivation: A Meta-Analytic Review", *Journal of Applied Psychology,* Vol. 87 No. 4, pp. 797–807.

Kartaszewicz-Grell, K. B., Adamowicz, M., Schiavone, F., Carr, S., Buysere, K. D., Marom, D., Zhang, B., Haverkamp, T., Qiao, J. and Shin, D. (2013). "The Crowdfunding Industry Report."

Kelion, L. (2014). "Kickstarter relaxes crowdfunding project rules." Retrieved 2015-03-17 from http://www.bbc.com/news/technology-27699267

Kickstarter (2014). "Introducing Launch Now and Simplified Rules." Retrieved 2014-10-10 from https://www.kickstarter.com/blog/introducing-launch-now-and-simplified-rules-0

Kickstarter, Inc. (2011). "Shortening the Maximum Project Length." Retrieved 2015-08-26 from https://www.kickstarter.com/blog/shortening-the-maximum-project-length

Kickstarter, Inc. (2015a). "Creator Handbook." Retrieved 2015-03-20 from https://www.kickstarter.com/help/handbook/

Kickstarter, Inc. (2015b). "Creator Questions." Retrieved 2015-11-26, 2015 from https://www.kickstarter.com/help/faq/creator+questions#faq_41830

Kickstarter, Inc. (2015c). "How to Get Featured on Kickstarter." Retrieved 2015-08-20 from https://www.kickstarter.com/blog/how-to-get-featured-on-kickstarter

Kickstarter, Inc. (2015d). "Introducing Spotlight." Retrieved 2015-03-28 from https://www.kickstarter.com/blog/introducing-spotlight

Kickstarter, Inc. (2015e). "Kickstarter Stats." Retrieved 2015-03-23 from https://www.kickstarter.com/help/stats

King, M. F. and Balasubramanian, S. K. (1994), "The Effects of Expertise, End Goal, and Product Type on Adoption of Preference Formation Strategy", *Journal of the Academy of Marketing Science,* Vol. 22 No. 2, pp. 146-159.

Kirmani, A. and Rao, A. R. (2000), "No Pain, No Gain: A Critical Review of the Literature on Signaling Unobservable Product Quality", *Journal of Marketing,* Vol. 64 No. 2, pp. 66-79.

Kirsch, L. J. (1996), "The Management of Complex Tasks in Organizations: Controlling the Systems Development Process", *Organization Science,* Vol. 7 No. 1, pp. 1-21.

Kirsch, L. J. (1997), "Portfolios of control modes and IS project management", *Information Systems Research,* Vol. 8 No. 3, pp. 215-239.

Kirsch, L. J., Sambamurthy, V., Ko, D.-G. and Purvis, R. L. (2002), "Controlling information systems development projects: The view from the client", *Management Science,* Vol. 48 No. 4, pp. 484-498.

Klotz, A. C. and Neubaum, D. O. (2015), "Research on the Dark Side of Personality Traits in Entrepreneurship: Observations from an Organizational Behavior Perspective", *Entrepreneurship Theory and Practice,* Vol. (forthcoming).

Korunka, C., Frank, H., Lueger, M. and Mugler, J. (2003), "The Entrepreneurial Personality in the Context of Resources, Environment, and the Startup Process—A Configurational Approach", *Entrepreneurship Theory and Practice,* Vol. 28 No. 1, pp. 23-42.

Krishnan, B. C. and Hartline, M. D. (2001), "Brand equity: is it more important in services?", *Journal of Services Marketing,* Vol. 15 No. 5, pp. 328-342.

Kuan, K. K. Y., Zhong, Y. and Chau, P. Y. K. (2014), "Informational and Normative Social Influence in Group-Buying: Evidence from Self-Reported and EEG Data", *Journal of Management Information Systems,* Vol. 30 No. 4, pp. 151-178.

Kuppuswamy, V. and Bayus, B. L. (2014), "Crowdfunding Creative Ideas: The Dynamics Of Project Backers In Kickstarter", *Working Papers / UNC Kenan-Flagler Research,* Vol. Paper No. No. 2013-15.

Lampe, J. C. (2004), "Alternative Personality Measurements Commentary on Accounting Information Systems Research Opportunities Using Personality Type Theory and the Myers-Briggs Type Indicator", *Journal of Information Systems,* Vol. 18 No. 1, pp. 21-34.

Lau, G. T. and Ng, S. (2001), "Individual and situational factors influencing negative word-of-mouth behaviour", *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration,* Vol. 18 No. 3, pp. 163-178.

Lecher, C. (2014). "How did a $10 potato salad Kickstarter raise more than $30,000?" Retrieved 2015-03-15 from http://www.theverge.com/2014/7/7/5878093/kickstarter-potato-salad

Li, F., Huang, M., Yang, Y. and Zhu, X. (2011), "Learning to identify review spam", in *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, Vol. 22, p. 2488.

Li, X. and Hitt, L. M. (2008), "Self-selection and information role of online product reviews", *Information Systems Research,* Vol. 19 No. 4, pp. 456-474.

Lin, M., Prabhala, N. R. and Viswanathan, S. (2013a), "Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending", *Management Science,* Vol. 59 No. 1, pp. 17-35.

Lin, M. and Viswanathan, S. (2015), "Home Bias in Online Investments: An Empirical Study of an Online Crowdfunding Market", *Management Science,* Vol. 62 No. 5, pp. 1393-1414.

Lin, M. F., Lucas, H. C. and Shmueli, G. (2013b), "Too Big to Fail: Large Samples and the p-Value Problem", *Information Systems Research,* Vol. 24 No. 4, pp. 906-917.

Little, J. D. (1979), "Aggregate advertising models: The state of the art", *Operations research,* Vol. 27 No. 4, pp. 629-667.

Liu, L., Borman, M. and Gao, J. (2014), "Delivering complex engineering projects: Reexamining organizational control theory", *International Journal of Project Management,* Vol. 32 No. 5, pp. 791-802.

Liu, Y. (2006), "Word of mouth for movies: Its dynamics and impact on box office revenue", *Journal of Marketing,* Vol. 70 No. 3, pp. 74-89.

Long, J. S. (1997), *Regression Models for Categorical and Limited Dependent Variables,* SAGE Publications.

Loughran, T. and McDonald, B. (2011), "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks", *The Journal of Finance,* Vol. 66 No. 1, pp. 35-65.

Loughran, T. and McDonald, B. (2013), "IPO first-day returns, offer price revisions, volatility, and form S-1 language", *Journal of Financial Economics,* Vol. 109 No. 2, pp. 307-326.

Love, I. and Zicchino, L. (2006), "Financial development and dynamic investment behavior: Evidence from panel VAR", *The Quarterly Review of Economics and Finance,* Vol. 46 No. 2, pp. 190-210.

Luca, M. and Zervas, G. (2013), "Fake it till you make it: Reputation, competition, and Yelp review fraud", *Harvard Business School NOM Unit Working Paper,* No. 14-006.

Luca, M. and Zervas, G. (2016), "Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud", *Management Science,* Vol. forthcoming.

Luo, X. (2009), "Quantifying the long-term impact of negative word of mouth on cash flows and stock prices", *Marketing Science,* Vol. 28 No. 1, pp. 148-165.

Luo, X. and Zhang, J. (2013), "How Do Consumer Buzz and Traffic in Social Media Marketing Predict the Value of the Firm?", *Journal of Management Information Systems,* Vol. 30 No. 2, pp. 213-238.

Luo, X., Zhang, J. and Duan, W. (2013), "Social media and firm equity value", *Information Systems Research,* Vol. 24 No. 1, pp. 146-163.

MacMillan, I. C., Siegel, R. and Narasimha, P. N. S. (1985), "Criteria Used by Venture Capitalist to Evaluate New Venture Proposals", *Journal of Business Venturing,* Vol. 1 No. 1, pp. 119-128.

Maddi, S. R. (1989), *Personality theories: A comparative analysis,* Dorsey Press.

Mahajan, V., Muller, E. and Kerin, R. A. (1984), "Introduction Strategy for New Products with Positive and Negative Word-of-Mouth", *Management Science,* Vol. 30 No. 12, pp. 1389-1404.

Massolution (2015). "The Crowdfunding Industry Report." Retrieved 2015-11-25 from http://reports.crowdsourcing.org/index.php?route=product/product&product_id=54 &tracking=5522f117147a6

Maurer, C. and Tiwana, A. (2012), "Control in App Platforms: The Integration-Differentiation Paradox", *International Conference on Information Systems (ICIS 2012)*, Orlando, USA.

Mavlanova, T., Benbunan-Fich, R. and Koufaris, M. (2012), "Signaling theory and information asymmetry in online commerce", *Information & Management,* Vol. 49 No. 5, pp. 240-247.

Mayzlin, D., Dover, Y. and Chevalier, J. A. (2012), "Promotional reviews: An empirical investigation of online review manipulation", National Bureau of Economic Research.

McCrae, R. R. and Costa Jr, P. T. (1997), "Conceptions and correlates of openness to experience", in Hogan, R., Johnson, J. and Briggs, S. (Eds.) *Handbook of Personality Psychology*, Academic Press, San Diego, pp. 825–847.

McCrae, R. R. and Costa Jr, P. T. (1999), "A Five-Factor Theory of Personality", in Pervin, L. A. and John, O. P. (Eds.) *Handbook of Personality: Theory and Research*, Guilford, New York, pp. 139-153.

McElroy, J. C., Hendrickson, A. R., Townsend, A. M. and DeMarie, S. M. (2007), "Dispositional Factors in Internet Use: Personality Versus Cognitive Style", *MIS Quarterly,* Vol. 31 No. 4, pp. 809-820.

Mearian, L. (2016). "Indiegogo launches crowdsourcing for big businesses." Retrieved 2015-06-05 from http://www.computerworld.com/article/3019349/emerging-technology/indiegogo-launches-crowdsourcing-for-big-businesses.html

Miller, D. (2015), "A Downside to the Entrepreneurial Personality?", *Entrepreneurship Theory and Practice,* Vol. 39 No. 1, pp. 1-8.

Mitroff, S. (2012). "Android Is Bigger, But Here's Why Apple Is Still the Undisputed App Cash King." Retrieved 2015-04-02 from http://www.wired.com/2012/12/ios-vs-android/

Mollick, E. (2014), "The dynamics of crowdfunding: An exploratory study", *Journal of Business Venturing,* Vol. 29 No. 1, pp. 1-16.

Moon, Y. and Nass, C. (1996), "How "Real" Are Computer Personalities? Psychological Responses to Personality Types in Human-Computer Interaction", *Communication Research,* Vol. 23 No. 6, pp. 651-674.

Moss, T. W., Neubaum, D. O. and Meyskens, M. (2015), "The Effect of Virtuous and Entrepreneurial Orientations on Microfinance Lending and Repayment: A Signaling Theory Perspective", *Entrepreneurship Theory and Practice,* Vol. 39 No. 1, pp. 27-52.

Nass, C. and Lee, K. M. (2001), "Does Computer-Synthesized Speech Manifest Personality? Experimental Tests of Recognition, Similarity-Attraction, and Consistency-Attraction", *Journal of Experimental Psychology: Applied,* Vol. 7 No. 3, pp. 171-181.

Nass, C., Moon, Y., Fogg, B., Reeves, B. and Dryer, D. C. (1995), "Can computer personalities be human personalities?", *International Journal of Human-Computer Studies,* Vol. 43 No. 2, pp. 223-239.

Nunnelly, A. (2013). "Ubuntu Edge Campaign Smashes Indiegogo Records." Retrieved 2015-03-23 from https://go.indiegogo.com/blog/2013/07/ubuntu-edge-campaign-smashes-indiegogo-records.html

Ondrus, J., Gannamaneni, A. and Lyytinen, K. (2015), "The Impact of Openness on the Market Potential of Multi-Sided Platforms: A Case Study of Mobile Payment Platforms", *Journal of Information Technology*.

Ouchi, W. G. (1979), "A Conceptual Framework for the Design of Organizational Control Mechanisms", *Management Science,* Vol. 25 No. 9, pp. 833-848.

Patrakosol, B. and Lee, S. M. (2013), "Information richness on service business websites", *Service Business,* Vol. 7 No. 2, pp. 329-346.

Pham, M. T. (1998), "Representativeness, relevance, and the use of feelings in decision making", *Journal of consumer research,* Vol. 25 No. 2, pp. 144-159.

Phillips, P. C. B. and Perron, P. (1988), "Testing for a unit root in time series regression", *Biometrika,* Vol. 75 No. 2, pp. 335-346.

Poetz, M. K. and Schreier, M. (2012), "The value of crowdsourcing: can users really compete with professionals in generating new product ideas?", *Journal of Product Innovation Management,* Vol. 29 No. 2, pp. 245-256.

Rakesh, V., Choo, J. and Reddy, C. K. (2015), "What motivates people to invest in crowdfunding projects? recommendation using heterogeneous traits in kickstarter", in *ser. International AAAI Conference on Weblogs and Social Media. ACM*.

Rochet, J.-C. and Tirole, J. (2003), "Platform Competition in Two-Sided Markets", *Journal of the European Economic Association,* Vol. 1 No. 4, pp. 990-1029.

Rosen, S. (1981), "The Economics of Superstars", *The American Economic Review,* Vol. 71 No. 5, pp. 845-858.

Rysman, M. (2009), "The economics of two-sided markets", *The Journal of Economic Perspectives*, pp. 125-143.

Schmalensee, R. and Evans, D. S. (2007), "The Industrial Organization of Markets with Two-Sided Platforms", *Competition Policy International,* Vol. 3 No. 1, pp. 151-179.

Schöndienst, V., Kulzer, F. and Günther, O. (2012a), "Like Versus Dislike: How Facebook's Like-Button Influences People's Perception of Product and Service Quality", in *International Conference on Information Systems (ICIS 2012)*, Orlando, USA.

Schöndienst, V., Kulzer, F. and Günther, O. (2012b), "Like Versus Dislike: How Facebook's Like-Button Influences People's Perception of Product and Service Quality", in *Thirty Third International Conference on Information Systems*, Orlando.

Schwienbacher, A. and Larralde, B. (2012), "Crowdfunding of small entrepreneurial ventures", in Cumming, D. (Ed.) *The Oxford Handbook of Entrepreneurial Finance*, Oxford University Press, pp. 369-391.

Shane, S. and Cable, D. (2002), "Network Ties, Reputation, and the Financing of New Ventures", *Management Science,* Vol. 48 No. 3, pp. 364-381.

Shi, Z. and Whinston, A. B. (2013), "Network structure and observational learning: evidence from a location-based social network", *Journal of Management Information Systems,* Vol. 30 No. 2, pp. 185-212.

Short, J. C., Broberg, J. C., Cogliser, C. C. and Brigham, K. C. (2010), "Construct Validation Using Computer-Aided Text Analysis (CATA): An Illustration Using Entrepreneurial Orientation", *Organizational Research Methods,* Vol. 13 No. 2, pp. 320-347.

Simonsohn, U. and Ariely, D. (2008), "When rational sellers face nonrational buyers: evidence from herding on eBay", *Management Science,* Vol. 54 No. 9, pp. 1624-1637.

Snell, S. A. (1992), "Control Theory in Strategic Human Resource Management: The Mediating Effect of Administrative Information", *Academy of Management Journal,* Vol. 35 No. 2, pp. 292-327.

Spence, M. (1973), "Job Market Signaling", *The Quarterly Journal of Economics,* Vol. 87 No. 3, pp. 355-374.

Spence, M. (2002), "Signaling in Retrospect and the Informational Structure of Markets", *The American Economic Review,* Vol. 92 No. 3, pp. 434-459.

Steuer, E. (2013a). "How to buy friends and influence people on Facebook." Retrieved 2016-06-05 from http://www.wired.com/2013/04/buy-friends-on-facebook/

Steuer, E. (2013b). "How to buy friends and influence people on Facebook." Retrieved 2015-03-23 from http://www.wired.com/2013/04/buy-friends-on-facebook/

Stewart, W. H., Jr. and Roth, P. L. (2001), "Risk Propensity Differences Between Entrepreneurs and Managers: A Meta-Analytic Review", *Journal of Applied Psychology,* Vol. 86 No. 1, pp. 145-153.

Stieglitz, S. and Dang-Xuan, L. (2013), "Emotions and information diffusion in social media—Sentiment of microblogs and sharing behavior", *Journal of Management Information Systems,* Vol. 29 No. 4, pp. 217-248.

Stiglitz, J. E. (1990), "Peer Monitoring and Credit Markets", *The World Bank Economic Review,* Vol. 4 No. 3, pp. 351-366.

Stock, J. H. and Watson, M. W. (2001), "Vector autoregressions", *Journal of Economic perspectives,* Vol. 15 No. 4, pp. 101-115.

Stuart, R. W. and Abetti, P. A. (1990), "Impact of entrepreneurial and management experience on early performance", *Journal of Business Venturing,* Vol. 5 No. 3, pp. 151-162.

Sudek, R. (2006), "Angel Investment Criteria", *Journal of Small Business Strategy Vol,* Vol. 17 No. 2, pp. 89-103.

Sun, H. (2013), "A longitudinal study of herd behavior in the adoption and continued use of technology", *MIS Quarterly,* Vol. 37 No. 4, pp. 1013-1041.

Tausczik, Y. R. and Pennebaker, J. W. (2010), "The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods", *Journal of Language and Social Psychology,* Vol. 29 No. 1, pp. 24-54.

Thies, F., Wessel, M. and Benlian, A. (2014), "Understanding the Dynamic Interplay of Social Buzz and Contribution Behavior within and between Online Platforms – Evidence from Crowdfunding", in *International Conference on Information Systems (ICIS 2014)*, Auckland, New Zealand.

Tirunillai, S. and Tellis, G. J. (2012), "Does chatter really matter? Dynamics of user-generated content and stock performance", *Marketing Science,* Vol. 31 No. 2, pp. 198-215.

Tiwana, A. (2014), *Platform Ecosystems: Aligning Architecture, Governance, and Strategy,* Morgan Kaufmann, Waltham.

Tiwana, A. (2015), "Evolutionary Competition in Platform Ecosystems", *Information Systems Research,* Vol. 26 No. 2, pp. 266-281.

Tiwana, A. and Keil, M. (2009), "Control in internal and outsourced software projects", *Journal of Management Information Systems,* Vol. 26 No. 3, pp. 9-44.

Tiwana, A., Konsynski, B. and Bush, A. A. (2010), "Research commentary-Platform evolution: Coevolution of platform architecture, governance, and environmental dynamics", *Information Systems Research,* Vol. 21 No. 4, pp. 675-687.

Toubia, O. and Stephen, A. T. (2013), "Intrinsic vs. image-related utility in social media: Why do people contribute content to twitter?", *Marketing Science,* Vol. 32 No. 3, pp. 368-392.

Tucker, C. and Zhang, J. (2011), "How Does Popularity Information Affect Choices? A Field Experiment", *Management Science,* Vol. 57 No. 5, pp. 828-842.

van der Linden, D., te Nijenhuis, J. and Bakker, A. B. (2010), "The General Factor of Personality: A meta-analysis of Big Five intercorrelations and a criterion-related validity study", *Journal of Research in Personality,* Vol. 44 No. 3, pp. 315-327.

Wareham, J., Fox, P. B. and Cano Giner, J. L. (2014), "Technology Ecosystem Governance", *Organization Science,* Vol. 25 No. 4, pp. 1195-1215.

Watson, D. and Clark, L. A. (1997), "Extraversion and its positive emotional core", in Hogan, R., Johnson, J. and Briggs, S. (Eds.) *Handbook of Personality Psychology*, Academic Press, New York, pp. 767 - 794.

Wessel, M., Thies, F. and Benlian, A. (2015a), "The Effects of Relinquishing Control in Platform Ecosystems: Implications from a Policy Change on Kickstarter", in *International Conference on Information Systems (ICIS 2015)*, Fort Worth, Texas, Vol. 36.

Wessel, M., Thies, F. and Benlian, A. (2015b), "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.

Wessel, M., Thies, F. and Benlian, A. (2016), "The Emergence and Effects of Fake Social Information: Evidence from Crowdfunding", *Decision Support Systems,* Vol. 90, pp. 75-85.

Wikimedia Foundation, Inc. (2015). "Lists of common misspellings." Retrieved 2015-04-05 from http://en.wikipedia.org/wiki/Wikipedia:Lists_of_common_misspellings/For_machines

Wojnicki, A. C. and Godes, D. (2008), "Word-of-Mouth as Self-Enhancement", *HBS Marketing Research Paper,* Vol. No. 06-01.

Wolter, C. and Veloso, F. M. (2008), "The effects of innovation on vertical structure: Perspectives on transaction costs and competences", *Academy of Management Review,* Vol. 33 No. 3, pp. 586-605.

Wright, P. L. (1973), "The Cognitive Processes Mediating Acceptance of Advertising", *Journal of Marketing Research (JMR),* Vol. 10 No. 1, pp. 53-62.

Yarkoni, T. (2010), "Personality in 100,000 Words: A large-scale analysis of personality and word use among bloggers", *Journal of Research in Personality,* Vol. 44 No. 3, pp. 363-373.

Yen, H. R. (2006), "Risk-reducing signals for new online retailers: a study of single and multiple signalling effects", *International Journal of Internet Marketing and Advertising,* Vol. 3 No. 4, pp. 299-317.

Yoffie, D. B. and Kwak, M. (2006), "With friends like these: the art of managing complementors", *Harvard Business Review,* Vol. 84 No. 9, pp. 88-98.

Zaheer, S., Albert, S. and Zaheer, A. (1999), "Time scales and organizational theory", *Academy of Management Review,* Vol. 24 No. 4, pp. 725-741.

Zhang, J. (2006), "The roles of players and reputation: Evidence from eBay online auctions", *Decision Support Systems,* Vol. 42 No. 3, pp. 1800-1818.

Zhang, J. J. and Liu, P. (2012), "Rational Herding in Microloan Markets", *Management Science,* Vol. 58 No. 5, pp. 892-912.

Zhu, F. and Zhang, X. (2010), "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics", *Journal of Marketing,* Vol. 74 No. 2, pp. 133-148.

Zimmerman, M. A. and Zeitz, G. J. (2002), "Beyond survival: Achieving new venture growth by building legitimacy", *Academy of Management Review,* Vol. 27 No. 3, pp. 414-431.

Appendix 1: Characteristics of Electronic Word-of-Mouth and Popularity Information

Table 17: Electronic Word-of-Mouth and Popularity Information

Characteristic	Electronic Word-of-Mouth (eWOM)	Popularity Information (PI)
Source	Opinion-based or preference-based social interactions; depending on consumer experiences or opinions	Action-based or behavior-based social interactions; depending on past consumer behavior
Author/creator of content/signals	Consumers/users; author can often be identified	Reported by platform providers based on user actions
Information collection	Direct or indirect communication	Observation
Information content	High; mostly qualitative	Low; mostly quantitative
Media richness	Text, pictures, videos (multimedia)	(Predominantly) text-based
Objectivity	Potentially biased	Depicts actual behavior
Level of aggregation	Aggregated on user level	Discrete

Appendix 2: Sentiment Analysis of eWOM Messages

A critical assumption for our hypotheses is that the majority of eWOM messages shared about crowdfunding campaigns have a positive or neutral valence, as it is unlikely that consumers have had negative experiences with the offered but not yet available products or services during the campaign runtime. To verify this assumption, we conducted a lexicon-based sentiment analysis for a random sample of 20,000 campaign comments and 20,000 Facebook shares, during which each word in the respective eWOM message was matched against a lexicon containing words with negative and positive sentiment. The AFINN, a human-designed lexicon used for this analysis, contains 2,477 words and phrases that are scored from +1 to +5 if positive and from -1 to -5 if negative, depending on the strength estimation, which is determined based on the psychological reaction of a person to a specific word or phrase (Stieglitz and Dang-Xuan, 2013). The results in Table 18 show that the vast majority of comments and Facebook shares do indeed contain positive or neutral text.

Table 18: eWOM Sentiment Analysis

	Length in characters	Sentiment score	Sentiment		
	Mean (SD)	Mean (SD)	Positive	Neutral	Nega-tive
Comments	126.73(115.25)	1.63 (1.22)	15,016	4,378	606
FacebookShares	445.94 (769.02)	1.15 (1.01)	13,211	6,373	416

Note: Sample of 20,000 comments associated with a campaign and 20,000 Facebook shares containing a hyperlink to a campaign on Indiegogo. Scores for every positive or negative word found in a specific text were totaled and divided by the total number of matches in the relevant text. The texts were considered positive if the total score was +1 or higher and negative if the total score was -1 or lower. Otherwise, the valence was considered to be neutral.

Appendix 3: Test for Stationarity in Time Series

The Phillips-Perron unit root in Table 19 is appropriate, as it allows unbalanced data. The null hypothesis that the panels contain unit roots is rejected for all variables.

Table 19: Phillips-Perron Unit Root Test

	P-Statistic: Inv. Chi^2	*p*-Values
Backers	2.00e+05	0.0000
FacebookShares	3.23e+04	0.0000
Comments	1.67e+05	0.0000

Appendix 4: Generalized forecast error variance decomposition (GFEVD)

Table 20: GFEVD for *Backers*

Forecast in days	*Backers*	*FacebookShares*	*Comments*
10	0.972707	0.0056135	0.0216795
20	0.9487129	0.0100427	0.0412444
30	0.9382321	0.0117736	0.0499943
40	0.9347897	0.0122837	0.0529265
50	0.9338259	0.0124125	0.0537616
60	0.9336073	0.012439	0.0539536

Note: Percent of variation in the Backers variable explained by column variable (10 to 60 days ahead).

Table 21: GFEVD for *FacebookShares*

Forecast in days	*Backers*	*FacebookShares*	*Comments*
10	0.1319028	0.8632971	0.0048001
20	0.1362664	0.8524516	0.011282
30	0.1373789	0.8482406	0.0143805
40	0.1376131	0.8469804	0.0154066
50	0.1376571	0.8466548	0.0156881
60	0.1376648	0.8465779	0.0157573

Note: Percent of variation in the FacebookShares variable explained by column variable (10 to 60 days ahead).

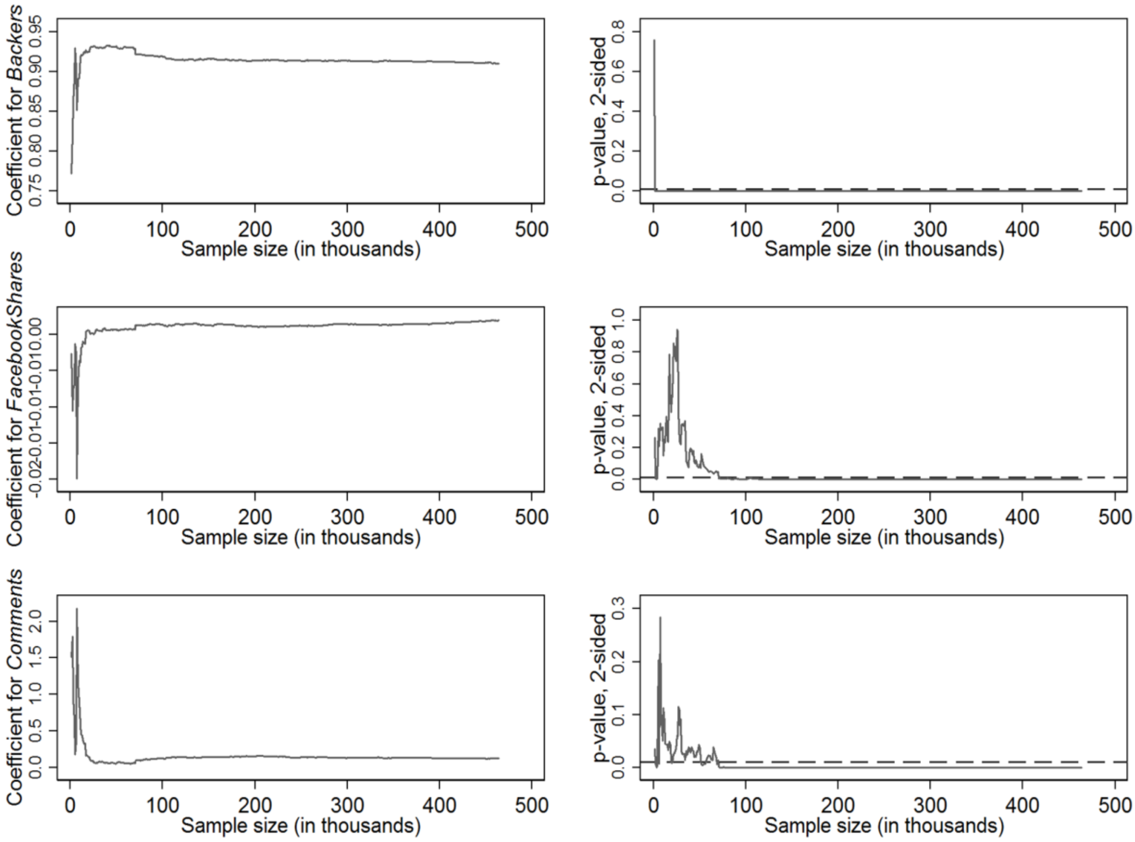
Table 22: GFEVD for *Comments*

Forecast in days	*Backers*	*FacebookShares*	*Comments*
10	0.025259	0.001191	0.9735499
20	0.0256176	0.0012628	0.9731196
30	0.0257231	0.0012859	0.972991
40	0.0257494	0.0012921	0.9729586
50	0.0257553	0.0012936	0.9729511
60	0.0257565	0.0012939	0.9729496

Note: Percent of variation in the Comments variable explained by column variable (10 to 60 days ahead).

Appendix 5: Coefficient/p-value/sample size (CPS) Charts to Check Robustness

Lin et al. (2013b) pointed out that studies with a very large sample size such as ours should not solely rely on *p*-values, as this might lead to a claim of support for hypotheses with no practical significance. We followed their practice and provide coefficient/*p*-value/sample size (CPS) charts to illustrate that our results are not based on sample size but hold for random subsampling. To generate those charts, we divided our sample into 500 parts, calculated our baseline model with a randomly chosen 0.2% of the total sample, and stored the beta coefficient, *p*-value, and sample size. We added another randomly selected 0.2% of the total sample and repeated the procedure. This process was repeated 500 times until we reached 100% of the sample. We plotted the resulting 500 coefficients and corresponding *p*-values to create Figure 11, which clearly indicates that the significant *p*-values and coefficients are not a mere result of sample size.



Note: Horizontal dashed line corresponds to p<0.01

Figure 11: CPS Chart for *Backers*: Coefficients and p-Values vs. Sample Size