TOWARDS INTERNALIZING THE EXTERNALITIES OF OVERFUNDING – INTRODUCING A 'TAX' ON CROWDFUNDING PLATFORMS

Research paper

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Abstract

Crowdfunding platforms offer project initiators the opportunity to acquire monetary resources from the Internet crowd and therefore have become a valuable alternative to traditional sources of funding. However, some processes on crowdfunding platforms cause undesirable external effects that influence the funding success of projects. In this context, we focus on the phenomenon of project overfunding. Massively overfunded projects have been discussed to overshadow other crowdfunding projects which in turn receive less money. We propose a taxation mechanism to internalize these overfunding externalities and to improve overall funding results. To evaluate this concept, we develop and deploy a sophisticated agent-based model (ABM). This ABM is based on a multi-attribute decision-making (MADM) approach and is appropriate to simulate the dynamic funding processes of a crowdfunding platform. Our evaluation provides evidence that possible modifications of the crowdfunding mechanisms bear the chance to optimize funding results and to alleviate existing flaws.

Keywords: Crowdfunding, Crowdlending, Crowdinvesting, Overfunding, External Effects, Internalization of Externalities, Pigouvian Tax, Agent-based Modeling, Market Engineering.

1 Introduction

The increasing availability of the Internet has continuously functioned as an important driver of innovative solutions as well as business models (Dijkman et al., 2015; Timmers, 1998; Gomber et al., 2017). The idea of asking a large crowd of people to support a certain cause was not new, but the far-reaching connective power of the Internet has liven up this concept and turned it into a powerful alternative to traditional ways of financing, such as bank credits or venture capital. The fast and dynamic ascent of crowd-based approaches of acquiring capital, like crowdfunding, crowdinvesting, or P2P lending, has attracted attention not only of the capital-seeking individuals but also of Information Systems (IS) research. Online crowdfunding platforms, i.e., the digital meeting places for money-seeking individuals and potential funders, constitute dynamic two-sided markets that bear many interesting and yet unexplored phenomena. The main focus of research has been so far on the analysis of available archival data (e.g., Koch and Siering, 2015; Mollick, 2014; Zvilichovsky et al., 2015), acquired survey data (e.g., Allison et al., 2014; Gerber et al., 2012), or experimental data (e.g., Burtch et al., 2015; Cholakova and Clarysse, 2015). The respective research questions that have been dealt with are addressing specific phenomena that are represented by actual data, such as the funding success of projects, the funding behavior of funders, or the motivations of individuals for participating in crowdfunding. Although it has been shown that crowdfunding has a high social value for society and for individuals that need financial support (Burtch and Chan, 2014), some processes on crowdfunding platforms cause undesirable externalities. However, the questions of how crowdfunding can serve best all of its stakeholders (Koch, 2017) or of how to deal with negative externalities are completely under-researched. Answers to these questions are of high value for society and of special importance for platform operators since the value of crowdfunding might be considerably increased. The “designer of electronic markets want to achieve a certain market outcome”, however, this outcome is “dependent on the behavior of all market participants” (Neumann et al., 2005). In IS literature, market engineering deals with the systematic and theoretically founded analysis, development, and optimization of electronic markets (Weinhardt et al., 2003) in order to reach a certain outcome by designing the market and its rules. With our research, we contribute to this stream of IS literature by addressing the question of how crowdfunding serves best all of its stakeholders. Specifically, we focus on the phenomenon of overfunding of crowdfunding campaigns (Koch, 2016), which is a consequence of funders’ behavior. In the case of overfunding, a crowdfunding project collects much more funding compared to the actual funding goal. In this context, it has been discussed, that overfunding can cause negative externalities for other projects which are overshadowed by overfunded blockbuster projects and thus suffer the disadvantage of collecting less money (Kim et al., 2016; Liu et al., 2015). We follow economic theory and propose a mechanism to internalize the externalities caused by overfunding. Specifically, we address the research question of *whether a taxation mechanism is able to improve overall funding results*. On that account, we propose the introduction of an on-platform “taxation” mechanism that allows for redistributing money to valuable underfunded projects to improve overall funding outcomes.

The analysis of archival or survey data is an important research tool and reveals interesting insights. Nevertheless, the interactive and dynamic interplay between a high number of individuals cannot be easily analyzed using this kind of data. Especially questions that concern the reaction to hypothetical environmental conditions cannot be answered only by considering such data. Thus, we deem it important that IS research uses its widely varied set of methods in order to address questions that could not have been answered so far in the field of crowdfunding. The effect of changes in market structure cannot be analyzed by available data and real tests would be highly costly for platforms. Against this backdrop, to evaluate our taxation approach, we propose a sophisticated agent-based model (ABM) reproducing and simulating a real platform system for analyzing the behavior of agents in the system. The outstanding advantage of this approach is its capability to simulate a real platform and agents' behaviors without effecting a real platform by experiments. With this powerful tool, we are able to evaluate our mechanism for internalizing overfunding externalities by applying sensitivity analysis.

We contribute to the literature on crowdfunding and market engineering by giving insights into an internalization mechanism that reduces overfunding externalities and increases the value of crowdfunding for its stakeholders. Thereby, we discuss and apply the related theory in this specific case. Furthermore, we give a clear and comprehensible outline of how to develop ABMs in the field of crowdfunding which could also be used for various other academic and practical question sets.

This paper proceeds as follows. Firstly, we provide important background information on crowdfunding and connected research, on the economic theory of the internalization of externalities in general and in the context of crowdfunding. Next, we provide information on our methodology as well as on how to develop an ABM for crowdfunding platforms, and we explain our approach of internalizing externalities of overfunding. Subsequently, we evaluate our model using sensitivity analysis and present our findings. Then, we discuss the results and the potential limitations, as well as provide an outlook on future research. Finally, we conclude.

2 Background

2.1 Crowdfunding and related IS research

The crowd-based acquisition of funding consists of asking a large crowd of people for their financial support and collecting their relatively small monetary contributions for accomplishing a certain financial goal. On online crowdfunding platforms, money-seeking project initiators ("project creators") meet potential funders ("backers") that are searching for interesting projects and promising investment opportunities. In order to convince funders to support their aims, project initiators present and describe their ideas using textual information, pictures, or videos. Typically, project initiators have to determine the funding goal (e.g., USD 20,000) and the length of the funding period (e.g., 30 days). If a project succeeds in reaching the funding goal by the end of the funding period, it is successfully funded. While some platforms pay out the money independently from reaching this goal (keep-it-all model, e.g., on giveforward.com), other platforms pay out the money only if the collected funding meets or exceeds the funding goal (all-or-nothing model, e.g., on kickstarter.com). Especially in the case of all-or-nothing models, which are applied on many platforms, high sums of collected funding have to be given back to the funders because the funding goal was not reached. According to which type of crowdfunding is applied, funders receive different types of compensation for their monetary support. While in reward-based crowdfunding funders pre-purchase material or immaterial (non-financial) compensations, e.g., products or services, in lending-based crowdfunding (P2P lending), funders receive repayments and interest payments. In equity-based crowdfunding (crowdinvesting), funders receive equities/shares of an enterprise. On the contrary, in donation-based crowdfunding, funders do not receive any compensation. However, the act of funding means psychological satisfaction through having helped other people altruistically (Gerber et al., 2012). Thus, funders derive a certain form of utility from supporting the projects even in this case of donations. The considerations concerning expected utilities are the main driver of the resulting funding decisions (Koch, 2017).

Research has already explicitly dealt with certain phenomena concerning individuals' funding decision behavior. It was found that especially friends and family members are among the first to support a project (Agrawal et al., 2015). Crowdfunding campaigns that have collected higher amounts of funding profit from a herding effect that drives people to further support the project because they trust the decisions of previous funders (Zhang and Liu, 2012). However, if a project is close to reaching the goal amount of money, some kind of bystander effect leads to the effect that funders "do not contribute to a project that has already received a lot of support because they assume that someone else will provide the remaining financing" (Kuppuswamy and Bayus, 2013). Investigations also show that funders "prefer to contribute funds locally and to culturally similar others" (Burtch et al., 2014). As a consequence of such funding decisions, some projects will reach their funding goal while others fail. Funding success can thus be interpreted as the aggregate result of the various funding decisions.

Research has also engaged in analyzing the drivers of crowdfunding success and found several interesting factors. Most basically, it was confirmed that lower funding goals are easier to reach than higher goals (Mollick, 2014). Less intuitively, it was revealed that longer funding periods of projects lead to a lower probability of funding success. It seems as if longer periods are interpreted as "a sign of lack of confidence" among project initiators (Mollick, 2014). Furthermore, evidence has been found for the importance of information provision. The more textual information is given, the more likely is funding success (Barbi and Bigelli, 2015; Koch and Siering, 2015; Pitschner and Pitschner-Finn, 2014). Moreover, pictures and graphical descriptions (Koch and Siering, 2015) as well as videos (Koch and Siering, 2015; Mollick, 2014) support funding success. These and other insights have been used, e.g., to predict campaigns' funding success (Koch and Cheng, 2016).

While such specific phenomena of crowdfunding have already gained attention in research, the superordinate question of how overall utility derived through crowdfunding could be optimized is still under-researched. From the perspective of practitioners, more specific propositions of how crowdfunding models could be enhanced are needed. Following the literature on market engineering, it is important to design electronic market places carefully and regarding individuals' behavior (e.g., Neumann et al., 2005; Weinhardt et al., 2003). This stream of IS literature deals with the analysis, development, and optimization of electronic markets (Weinhardt et al., 2003). For reaching a certain outcome, electronic markets need conscious design and rules. An interesting starting point for improving market outcomes on crowdfunding platforms is the great difference in funding amounts that projects receive. While some projects achieve very low levels of funding, other projects reveal massive overfunding (Koch, 2016). So far, the phenomenon of overfunding has been rarely addressed in research – however, if it was addressed, it was discussed controversially (e.g., Kim et al., 2016; Liu et al., 2015; Malave, 2012).

A statement that is regularly made in the context of overfunding is that it can cause externalities that have an impact on other projects on the platform. Here, both positive and negative external effects of overfunding are found and discussed (Doshi, 2014; Kim et al., 2016; Liu et al., 2015). One obvious reason for such effects is that crowdfunding projects on a platform compete for funding (Burtch, 2011). Money that is spent on one project cannot be received by another project. First of all, it has been confirmed that overfunded blockbuster projects have significant external effects on other projects (e.g., Kim et al., 2016; Liu et al., 2015). Here, it was shown that massively overfunded projects can have a positive effect on “related projects”. In other words, those projects that have a related topic profit from the existence of overfunded blockbuster projects (Kim et al., 2016; Liu et al., 2015). However, while “related projects” seem to benefit, it has been revealed that overfunded projects “hurt the performance of less-related projects” (Liu et al., 2015). As a consequence, a great number of projects is adversely influenced concerning the funding performance, since it can be assumed that there are typically more unrelated than related projects on a platform. Kim et al. (2016) confirm that there is a significant “cannibalization effect of blockbuster projects” on projects of other topics. Doshi (2014) even claims that project initiators choose the "option of not entering" the platform with a new project because they fear to be outshined by the blockbuster projects. Kim et al. (2016) also find indication that some project initiators refuse to start new projects on the platform if there are massively overfunded blockbuster projects. Such empirical findings make us believe that overfunding cannot just be seen as a positive phenomenon in crowdfunding. This opinion finds support by a range of further facts. Mollick (2014), for example, concludes that overfunded projects are "particularly vulnerable to delay" concerning the delivery of rewards. This constitutes a negative effect for funders who have to wait much longer for their funding compensations as promised. Moreover, there are well-known overfunded projects that have struggled and have left behind a big crowd of disappointed funders (like, e.g., the Coolest Cooler, or the video game console OUYA). Here, we argue that a concentration of funders on highly overfunded projects leads to a concentration of risk. If an overfunded project fails or cannot fulfill its promises concerning the rewards, it is more likely to trigger a ‘shit storm’ or negative publicity for the platform than a number of less funded projects. Such examples of negative external effects can be seen as possible symptoms of market failure (Williamson, 1971). As a result, the funding outcomes may be biased by market failure rather than reflecting optimal funding results (Koch, 2016).

2.2 Internalization of external effects

From a theoretical perspective, external effects or externalities are central to the "critique of market organization" (Buchanan and Stubblebine, 1962). Externalities are present when there is a "divergence between private and social costs" (Dahlman, 1979). If so, the utility of an individual is not only dependent on his/her own activities, but also on the activities of other individuals. Externalities can be positive or negative and they have a considerable impact on the transactions that are made on markets. Without intervention (i.e., internalizing the externalities), some potential beneficial transactions are not realized – which harms the performance of markets and leads to market failure (Dahlman, 1979). In economic theory, the internalization of externalities is a widely discussed approach to prevent market failure or to reduce its consequences for individuals and the society. For the elimination or reduction of external effects, elements of the Coasian (Coase, 1960) and the Pigouvian (Pigou, 1920) approaches are considered (Aidt, 1998). Both approaches have the goal to reallocate resources in order to eliminate or prevent market failure caused by external effects. While the Coasian approach encourages an efficient resource allocation through negotiation of the involved parties (Coase, 1960), the goal of the Pigouvian approach is to impose a tax – the so-called Pigouvian tax – on negative externalities, so that emerging external costs are carried by the perpetrator. Due to the tax, the economic acting and the behavior of the perpetrator is to be redirected in the desirable direction (Pigou, 1920).

As a practical proceeding for internalizing externalities, Gupta and Prakash (1993) propose four steps: (i) the (negative) externalities need to be recognized, (ii) the perpetrator and the potential victim must be identified, (iii) for each party, costs and benefits of internalization need to be evaluated, and (iv) the costs and benefits of internalization need to be assigned. For the assignment of costs and benefits, the policy maker needs to decide which mechanism to use. Since the mechanism depends on the purpose, different approaches were discussed in academic literature, e.g., for environmental policy (Baumol and Oates, 1971) or regulating systemic risk in the financial sector (Acharya et al., 2010). We argue that the internalization of external effects is also valuable to be discussed in crowdfunding context.

In the backdrop of having some crowdfunding projects worth to be funded which fail to reach their funding goal, we decide to contribute to the discussion by addressing the negative externalities of overfunded projects. We aim at clarifying whether a funding redistribution mechanism is able to improve funding outcomes on a platforms. Inspired by the Pigouvian tax, we develop a taxation approach that imposes a tax on funding that goes beyond a project's funding goal. However, according to the Pigouvian approach (Pigou, 1920), the tax needs to reflect the negative consequences that all other individuals experience. Instead, our approach primarily aims at achieving the best funding results and is not directly based on individuals' costs. This has the advantage that costs do not need to be expressed in monetary units. Moreover, the tax yield is not used to compensate all individuals' costs, but is distributed to selected valuable projects that have closely missed their funding goal. Thus, we do not claim to fulfill the requirements of the Pigouvian tax and just call it "tax" instead. Further, we are aware of that a tax usually is imposed by governments and that our approach represents a compensation payment used as market engineering instrument. Still, the functionality is inspired by a taxation approach. As actual platform data is not able to analyze the effect of such a tax, we choose an approach based on an agent-based model simulating the processes of a crowdfunding platform.

3 Analyzing an Internalization Approach for Crowdfunding

3.1 Methodology

For platform operators, it can turn out to be disadvantageous to run real tests on the platform for potential modifications or new models since this could possibly lead to unexpected consequences and costs. With ABMs' capabilities to simulate individuals' decision-making behavior, it is possible to model platforms in order to analyze the emergent reactions of its users, e.g., in case of modifications. Such investigations are of high value in the context of crowdfunding platforms. Agent-based modeling has become a widespread and common tool for analyzing complex socio-technical systems in diverse academic disciplines (Nikolic and Ghorbani, 2011). An important reason for this increase in applications is the fact that purely mathematical models have their limits when it comes to modeling complex dynamic systems that reveal diverse interactions, adaptations, or changing conditions (Bonabeau, 2002). Especially modeling heterogeneity, e.g., of individuals' decision-making behavior, is a big issue. In contrast to mathematical models, ABMs allow for the possibility to model numerous autonomous heterogeneous agents, whose behaviors are specified by certain rules. Using ABMs, it becomes possible to model large scale natural or human-made systems (Ballot et al., 2015; Macal and North, 2010) and to observe the collective effects of agents' behaviors and interactions. In economic models, equilibrium theories with strongly simplifying assumptions – like rational, homogeneous agents – are no longer a limitation to research if ABMs are applied (Macal and North, 2010).

Although ABMs have found their justified role in academic research, the implementation of ABMs for crowdfunding platforms in academic literature is surprisingly scarce. Research has mainly engaged in mathematical models (e.g., Alaei et al., 2016; Chang, 2016) so far. However, such models are disadvantageous when modeling the complex interplay of numerous agents on crowdfunding platforms. Thoroughly reviewing the literature on crowdfunding, we have discovered only two agent-based approaches. Yang et al. (2016) model the interactions among initiators, funders, and the crowdfunding platform – considering the dynamic process of crowdfunding. However, individuals' preferences and the decision-making are modeled rather rudimentary by pure random variables and do not regard specific characteristics of projects. Although funders are described as heterogeneous, they are homogeneous in terms of investment diversification. Lee et al. (2016) develop a basic ABM to test different methods of distributing donations. Therefore, they determine state variables based on data from different actual crowdfunding platforms. However, the decision of funders which project to support is completely randomly generated and is – again – not based on projects' characteristics. As a consequence, both models do not cover the important feature of funders' decision-making and a discussion of how to model agents' decision behavior more realistically is missing. We go further and propose a sophisticated ABM that covers a more realistically simulated decision-making behavior of agents.

Since the implementation of ABMs is challenging, research has already engaged with the questions of how ABMs are optimally developed and described. For the development of ABMs, Nikolic and Ghorbani (2011) propose to follow the steps of system analysis, model design and detailed design, software implementation, and model evaluation. While Nikolic and Ghorbani (2011) concentrate on a methodological framework for developing ABMs, Grimm et al. (2006) focus on the optimal description of ABMs. They propose the so-called ODD protocol for describing ABMs. This framework consists of an overview (ODD), the design concepts (ODD), and the specific details of the model (ODD). Developing our ABM, we apply and regard both guidelines.

At first, a *system analysis* (Section 3.2) must be performed regarding the real-world system – which is the crowdfunding platform in our case. At this point, we emphasize that existing research is a valuable source of important hints and necessary requirements that need to be regarded. It is true that the system analysis is in the area of ABM developers' responsibility; however, it is important and fruitful to consider existing work in this field. Based on the system analysis, the *model design* (Sec. 3.3) is developed. Here, we also include the logical elements of the *detailed design*. Furthermore, we regard the advice for describing ABMs given by Grimm et al. (2006) and consider the purpose of the model (Sec. 3.3.1), the state variables, scales, initialization, and input (Sec. 3.3.2), the process overview and scheduling (Sec.3.3.3), and the design concepts used (Sec. 3.3.4). Due to page limitation, we do not detail on the step of *software implementation* as this does not sufficiently contribute to the understanding of our ABM approach. Next, the model must undergo a *model evaluation* (Section 3.4). In this section, we also include the experimental design of the *detailed design* as stated in Nikolic and Ghorbani (2011). At this point, we perform a validation and verification of our model and compare the ABMs' results to the real-world system (Sec. 3.4.1). Next, we address our research question of whether a taxation mechanism is able to improve overall funding results on a crowdfunding platform (Sec. 3.4.2).

3.2 System analysis

The complexity of a crowdfunding platform mainly arises out of the big number of agents and objects involved and their multi-faceted interactions and behaviors. In crowdfunding, we can identify numerous stakeholders concerned (Koch, 2017). The main agents involved are platform operators, project initiators, and funders. The operators determine platform parameters and the funding mechanism. While initiators decide on how to design the crowdfunding campaigns, funders screen these campaigns and decide for funding or not. Moreover, social connections play an important role. The first funding contributions are usually made by family members and friends who often act because of "social obligation" (Agrawal et al., 2015). All other funders concentrate on information used for the presentation of projects and to the amount of funding that has already been reached (Agrawal et al., 2015; Koch and Siering, 2015; Kuppuswamy and Bayus, 2013; Mollick, 2014; Zhang and Liu, 2012). We emphasize that further effects, like the visibility of project presentations on the platform, advertising in social media, convincing comments, and update posts also play certain roles (Li and Duan, 2014). For details, we refer to the literature on crowdfunding in general (e.g., Beaulieu et al., 2015) and on specific effects, such as the herding effect (Zhang and Liu, 2012) or the bystander effect (Kuppuswamy and Bayus, 2013). When developing an ABM, simplifications are needed to handle the complexity. The decision of which effects are explicitly regarded in the model is described in the following section.

3.3 Model design

In our study, we concentrate on *reward-based crowdfunding* since we calibrate our model using original data from a reward-based crowdfunding platform. Moreover, we consider an *all-or-nothing* model because, here, failing to reach the funding goal has more serious consequences – compared to the *keep-it-all* model. On the platform, new crowdfunding campaigns are started and the funders are asked to support them. However, in the model, initiator agents are only explicitly needed if they reveal active behavior or if their activities are to be tracked. In our case, we focus on funding behavior and thus only consider the pool of projects that the funders choose from. We do not need to explicitly simulate the initiators. The campaigns reveal no actions or behaviors but certain characteristics and parameters. The funding success of a campaign depends on these properties and the respective decision-making of the funders. Campaigns' properties can be divided into three categories: (i) The first category encompasses the parameters that describe the project, i.e., the number of videos, the number of pictures, and the length of the textual description (*descriptive parameters*). Such aspects that are revealed by actual campaigns on platforms are explicitly modeled. These parameters do not change over time and are evaluated qualitatively similar by each funder. (ii) The second category consists of properties that change over time and are, thus, evaluated differently according to when they are regarded (*dynamic parameters*). These parameters are the amount of collected funding and the elapsed time of the funding period. (iii) The third category contains properties that are set by project start and are differently evaluated by the funders (*parameters of taste*). These are the project category and a unique parameter of taste. Transferred to the real world, this simulates, e.g., that a funder prefers projects concerning the category of music – but only a certain kind of music. In our opinion, funders' decision-making behavior constitute the core of the system. Funders decide whether to support a project or not based on the given parameters. A funder can be active or inactive – like on real platforms. In the first case, the agent takes part in funding; in the second case, there are no funding actions. A funder reveals several static properties, which are assigned at the beginning of the simulation. These properties encompass the likelihood of a funder being active, the number of projects being observed, the likelihood to participate in an initial funding, and the preferences for certain project categories. In order to simulate heterogeneous funders, the model attributes an individual preference parameter to each funder. If a funder's preference parameter is close to a campaign's taste parameter, the funder values the campaign higher.

Although the funding decision-making behavior is of central importance, previous ABM research has disregarded these behavioral aspects. Consequently, we propose a decision-making mechanism which is based on a method that is already well-established in research. In a first step, funders regard a certain number of randomly drawn projects that they could potentially support. This simulates the fact that a funder is not able to screen all projects but will only discover a limited number of projects (limited awareness). For example, some funders screen the projects for certain topics or use a keyword search. However, this limitation of funders' awareness can be adapted and means no restriction for the model. Next, there are two funding principles. First, for each time a funder becomes active, a random variable is drawn that determines whether the funder makes a normal or an initial funding. In case of an initial funding, the funder supports a randomly drawn project that was just started on the platform. This simulates an initial funding that is made by family members and friends. Such funding contributions are mostly independent from quality or descriptive parameters (Agrawal et al., 2015). However, this type of funding is less frequent. In case of a normal funding, campaigns' parameters are explicitly regarded. Here, we follow the multi-attribute decision-making (MADM) method by Xu (2015). This method uses the ordered weighted averaging (OWA) operator introduced by Yager (1988). The OWA operator regards a vector of n decision-relevant parameters. First, these parameters a_k of the vector are ordered by their size. Next, each element b_j of the ordered vector is multiplied by a certain predetermined weight w_j. Following the notation of Fullér (1996), the OWA operator is defined as follows:

$$F(a_1, \dots, a_k, \dots, a_n) = \sum_{j=1}^{n} w_j b_j \qquad \text{where } b_j \text{ is the } j-th \text{ largest element of a bag } < a_1, \dots, a_n >,$$
$$\text{and } w = (w_1, w_2, \dots, w_n)^T, \text{ with } w_i \in [0,1], 1 \le i \le n, \text{ and } \sum_{i=1}^{n} w_i = 1 .$$

The result can be interpreted as a certain value that is attributed to this set of parameters by a respective funder. Yager (1988) identifies two important concepts of the OWA operator: andness and orness. With a high orness, it is possible that properties can compensate each other. In case of a high andness, there is less compensation. The level of andness/orness results from the vector of weights and is able to imitate individuals' evaluations (Fullér, 1996). For our model, we choose the simplest setup of this vector, in which all weights are equal. In order to make the project properties appropriate for using the OWA operator, and according to the MADM method, the properties are normalized on an interval of [0,1]. Based on Xu (2015), we use the following formulas for normalization:

(i) benefit-type (high values preferred): $n_i = \frac{a_i - \min\{a_i\}}{\max\{a_i\} - \min\{a_i\}}$,

(ii) cost-type (low values preferred): $n_i = \frac{\max\{a_i\} - a_i}{\max\{a_i\} - \min\{a_i\}}$,

(iii) fixed-type* (values close to a fixed value α are preferred): $n_i = 1 - \frac{|a_i - \alpha|}{\max\{|a_i - \alpha|\}}$.

[Be careful – there are some issues with the notation used in Xu (2015).]*

The parameters of each campaign observed are normalized according to the respective types stated above. For example, the benefit-type is used for the number of pictures. Here, the more pictures are used, the more likely is a funding contribution (Koch and Siering, 2015). In the case of individual taste, the fixed type of normalization is used. The vectors of the normalized parameters are arranged in a decision matrix as proposed by Xu (2015). Subsequently, the OWA operator is used to evaluate each campaign. Then, the projects are sorted according to the evaluation and the best projects are chosen for funding. In contrast to the ABMs proposed so far, the funding decision-making is no longer purely random but is based on the parameters of the campaigns at choice. Finally, we expect that funders do not fund projects that are valued below a certain threshold. If the considered projects are valued below this threshold, a funder invests into an alternative investment opportunity (or consumes the money).

Effects that we explicitly regard are the effect of achieved funding (herding effect) and the effect of time lapsed (bystander effect). Following Li and Duan (2014), there exists the following relationship: The more time remains and the more money is pledged, the more likely funders support a project. To catch these effects, we use a formula that exactly reveals this behavior: $1 - (1 - \theta)^{-\log(d)} \in [0,1]$. Here, d is the percentage of time lapsed and θ is the proportion of the collected money relative to the goal. This parameter is normalized as a benefit-type. If the funding goal is finally reached, we expect that the intrinsic motivation to support a campaign to reach its goal vanishes.

3.3.1 Purpose

The purpose of our model is to address the question of how externalities of overfunded projects can be internalized. In order to address this question, we follow economic theory regarding the internalization of externalities, and develop a funding redistribution mechanism based on a tax on overfunded projects. Therefore, the aim is to evaluate this mechanism and to contribute to the discussion on how crowdfunding serves best all of its stakeholders. For this evaluation, the model needs to be as close to reality as possible and thus we consider a sophisticated decision-behavior mechanism. The existence of an alternative investment opportunity that funders choose if there are no highly valued projects is a detail that can be attributed to an environmental view. However, as a simplification, we disregard other inter-platform effects or environmental effects and take an on-platform view.

3.3.2 State variables, scales, initialization, and input

In the following, we discuss the variables that are used. Our ABM models a certain number of days (360). Each day, a certain number of projects is initialized on the platform following a Poisson distribution (λ=170). On the platform, a certain number of funders is registered (3,300,000). A funder gets active with an individual probability which is drawn from a uniform distribution of the interval [0,1]. Another random variable determines whether a funder does an initial funding (probability=0.02125) or a normal funding. A project can receive an initial funding at a maximum of three days after its foundation. Each funder observes a number of projects (1,000). The individual preference parameters of funders are drawn from a normal distribution applied to the interval [0,1] (mean=0.5, std=0.25). The amount of money a funder pledges when supporting a project is simulated by values drawn from a Poisson distribution (λ=80). These values constitute the budget constraints for funding. If there are no projects valued above or equal to a value of 0.65, a funder chooses an alternative investment opportunity off the platform.

The initialized campaigns reveal realistic funding periods following a distribution drawn from a real dataset of a crowdfunding platform. Furthermore, we draw the number of pictures, the text length of project descriptions, the number of videos, project durations, and category numbers using discrete distributions also derived from real datasets. All data for the distributions that we use is derived from kickstarter, one of the largest crowdfunding platforms. This data is then transformed to reasonable distributions by eliminating outliers. Only for the funding goal, we use a fixed goal of 15,000 for all projects in order to ensure a better comparability of the scenarios. If a distribution is chosen that leads to various different goals, the resulting rates of successfully funded projects vary a lot. In this case, longer simulation times are needed in order to achieve valid results. The goal of 15,000, however, is plausible and chosen according to typical funding goals on the platform kickstarter. Finally, projects' unique parameters of taste are randomly drawn following a uniform distribution of numbers of the interval [0,1]. The state variables are based on real data and calibrated to model reality properly.

3.3.3 Process overview and scheduling

The simulation starts with reading the configuration file for initializing as well as reading the data used for generating the distributions. Then, the funders are generated and the simulation starts. On each day campaigns are generated and all agents perform their daily routine. All expired projects are deleted by the end of the simulated day. Before the generated data of the simulation is saved, the program needs to be initialized. For this reason, the model is run 120 days without storing the data because right at the beginning there are only few projects active. After 120 days, the data is saved for the analysis.

First, for each funder, it is determined whether the funder becomes active or not. Then, if a funder is active, another random process determines whether a funder makes an initial funding or a normal funding. In case of an initial funding, the funder randomly draws a project independently from its valuation and funds it. In the case of a normal funding, a funder's choice of supporting projects is determined by the MADM and OWA decision mechanism, which was introduced above. Each funder supports the configured number of projects based on the resulting vector of evaluated projects.

3.3.4 Design concepts

The aim of discussing the design concepts is to classify the introduced ABM within complex adaptive systems and to check whether certain design parameters are implemented (Grimm et al., 2006). Bonabeau (2002) describes *emergence* as the result of the interaction of different agents in a system, where the result is more valuable than the components. In our model, the funding outcomes of the projects are such emergent phenomena because they are the result of a complex interaction process. The agents of our model are limited concerning their *adapting behavior*. The simulated projects do not reveal any adapting behavior. However, the funders adapt their funding choices to the projects available at the moment of evaluation. The concept of *fitness* considers how adjustments in the system lead to an optimal or better (economic) state. In our model, funders actively optimize their funding choice following their decision-making behavior and engage in supporting the best projects. For the design concept of *sensing*, all variables are considered that agents can observe. Funders decide based on the observed ("sensed") properties of the projects. Moreover, our model reveals *interactions*, for example, through the design that funders follow especially campaigns that have been funded before (herding). All these processes, and thus the main part of the model is based on *stochastic* distributions and random processes to assign properties to the different agents. Finally, the results of the simulation lead to certain observations. All simulation results are saved and are used for analyses. However, Grimm et al. (2006) do not underline the fact that design should also be aligned to theoretical considerations. As a consequence, we add the concept of *theoretical alignment* to the list and emphasize that the engagement with existing theories in the field is of high value for the conceptualization of an ABM. The advantage of theories is that they formulate important coherences and relationships that are often difficult to be directly observed in real-world systems. Our ABM is inspired by existing theories and considers important coherences in crowdfunding, like the herding effect or the bystander effect.

3.4 Evaluation of the model

The development of ABMs is no end in itself but is supposed to provide the basis for promising investigation opportunities. Therefore, an ABM needs to be evaluated so that possible flaws or limitations can be discovered and resolved. An important step in the development of ABMs is the verification and validation of the model. The *verification* addresses the question of whether the model does what it is intended to do (Nikolic and Ghorbani, 2011). Next, in the *validation*, it is checked whether "the modeled outcomes correspond with observed reality" (Nikolic and Ghorbani, 2011). The fact that ABMs are simplified models of real-world processes demands for certain simplifications. These simplifications, however, must not lead to distortions of models' outcomes. In order to calibrate our model, we choose a basic scenario that allows for comparing funding outcomes to real-world data. If the ABM is able to produce funding outcomes that are similar to actual funding outcomes of existing platforms, the processes implemented in the ABMs are able to imitate the relevant processes.

The main advantage of agent-based models is the opportunity to model and analyze complex systems which could not or not easily be captured by pure mathematical calculation, e.g., by applying stochastic equations. Applying simulated scenarios, an ABM can be used for experiments and fulfills two important tasks. First, an ABM can confirm or reject a conjecture. Therefore, some kind of input is given into the system and, finally, a specific output is received that allows for confirming or rejecting the conjecture. In a simple case, this may not bring forth an amazing miracle as the basic coherences are often clear and allow for an educated guess. However, second, the ABM can be used for a sensitivity analysis and for optimization problems. By (systematically) changing the input parameters, the characteristic responses from the system can be analyzed and be transformed to new insights about the system. Such inferences are important and of high value for decision situations. These insights can be used for developing rules of thumb or as a basis for managerial decisions. Consequently, the ABM becomes a powerful decision support tool of market engineering that aids, e.g., model design and price determination.

3.4.1 Verification and validation

Before trusting ABMs' results, literature advises to control for correctness and plausibility. Of course, it is difficult to reconstruct each single step processed in the simulations. However, it is possible to control the overall outcomes. Therefore, after running our model, we have printed the characteristic graph of funding outcomes that result from the model. This graph depicts the distribution of funding outcomes and shows how many projects have reached a certain level of funding. This distribution is regularly used in literature in order to gain an impression about how well projects are funded and what funding result they achieve relative to their funding goal determined. For example, a project with a funding goal of USD 8,000 that has collected USD 9,000 has achieved a funding level of 112.5%.

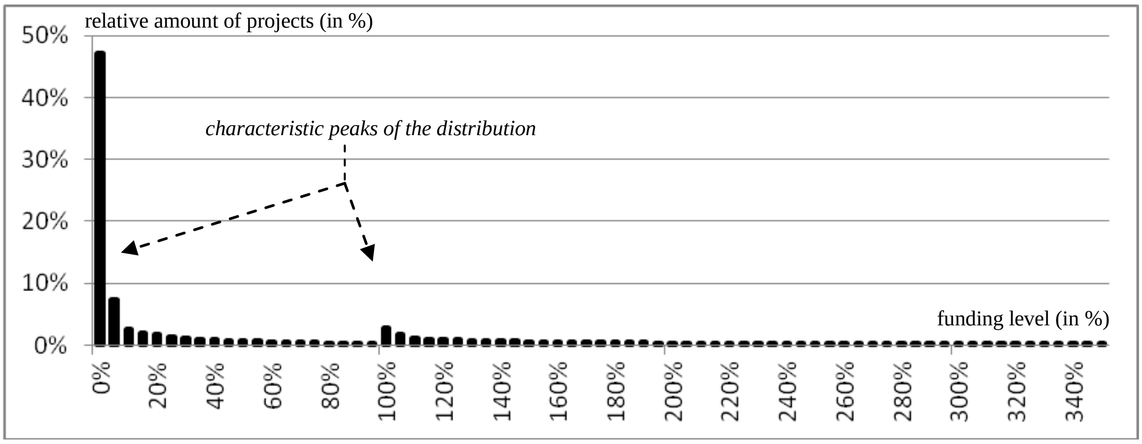

Figure 1. Resulting distribution of funding outcomes.

Figure 1 depicts the distribution of funding outcomes of our model for the basic scenario. There are two characteristic peaks close to 0% and 100% of funding. This result is supported by previous research, which has stated that among "crowdfunded projects, failures happen by large amounts, successes by small amounts" (Mollick, 2014). Comparing the distribution in this figure to those that have been published in other studies based on authentic data from platforms, we can see that the funding behavior modeled in our ABM reveals a similar distribution (Koch, 2016; Kuppuswamy and Bayus, 2013; Lu et al., 2014; Mollick, 2014). Consequently, we conclude that the ABM proposed is able to reproduce comparable funding results to those of actual platforms. The only difference of the results received by our configuration is, however, that we receive a slightly higher peak around a funding level of 0%. However, the level of funded projects can easily be increased if more funders are simulated. We intentionally use this setup of a lower efficiency to have a good starting point for analyzing the effect of introducing our tax mechanism in order to improve overall funding results.

3.4.2 Experimentation: applying a tax to overfunding

After having verified that our agent-based model delivers suitable results in the basic scenario, we conduct an experiment on introducing a tax on overfunding in order to internalize negative externalities. In our experimentation, we focus on our research question and address the phenomenon of project overfunding. As a practical alignment, we follow the four steps proposed by Gupta and Prakash (1993) for the process of internalizing externalities (Section 2.2). (i) Research analyses have recognized negative externalities resulting from overfunded projects on crowdfunding platforms (Kim et al., 2016; Liu et al., 2015). (ii) However, not the projects or initiators are the perpetrators that cause the negative externalities, but the funders who are the active deciders and choose to concentrate on blockbuster projects. By this focus, some projects become more visible and overshadow other projects. The victims of such behavior are projects that reveal less funding but also the funders of these projects because their favored projects are not completed. (iii) We argue that funding is beneficial when it helps a project to reach its funding goal, i.e., the required amount of money for the project. Money that succeeds this goal is mainly funded, because funders are massively attracted by the funding compensation, i.e., attractive rewards, and so they continue to fund (Koch, 2016). This part of funding, however, increases the visibility of this blockbuster project which distracts attention from other projects. Consequently, the funders need to carry the costs of putting only blockbuster projects in the middle of interest. (iv) According to our approach, individuals who continue funding will have to pay an additional tax τ on their funding. If the funding goal has been reached and a funder focuses on a reward for which s/he has to give an amount of money z, it has to be paid $z \cdot (1 + \tau)$ instead of z. This tax slightly increases the amount due for funders. All funders that contribute to the project before it reaches its funding goal do not need to pay this tax – funders that decide for supporting projects, which have already hit their funding goal, have to pay this additional tax on top of the normal funding. Thus, the tax will counter the buy-side pressure that focuses on the rewards. The resulting tax yield is redistributed to those projects that have closely missed their funding goal so that these are finally successfully funded – starting with the project closest to its goal. Thus, the funding that projects have reached serves as a proxy for quality in order to avoid funding of low-quality projects. Furthermore, funders are redirected to other projects in a Pigouvian manner because funding the blockbuster project is made less attractive. By this approach of internalizing externalities, the victims benefit from the tax. As long as there are enough funders who find funding alternatives or are willing to pay the additional tax, this mechanism will increase the number of successfully funded projects. The tax has an important advantage over funding caps or maximal funding amounts because the funders are still allowed to fund the projects of their interest and do not lose their favorite options.

In the ABM, the tax is implemented as a cost-type parameter. If the funding goal is reached, the tax τ is applied. Then, this aspect is evaluated with $1 - \alpha \cdot \tau$ by the funders. α is the parameter that defines how strong funders react to the increased price. In our experiment we choose $\alpha = 10$. This parameter allows for later adjustments in case of different platforms and culturally or behavioral different individuals that might reveal different reactions to higher prices. Next, we apply sensitivity analysis for estimating an appropriate level of the tax to enhance overall funding outcomes.

Figure 2 provides the result of our sensitivity analysis for different levels of a tax for overfunded projects. Firstly, we are able to show that the rate of successfully funded projects increases due to the redistribution (a). Moreover, we track both the sum (b) and the rate of successfully funded money (c), i.e., the part of money invested into successfully funded projects. The rate of successfully funded money is the rate of money that is given to projects that finally reach their funding goal. In other words, if this rate is 85%, 15% of the funding is refunded because the projects are not paid out the money (all-or-nothing model). While the first graph (a) reveals a positive consequence from introducing a tax (rising rate of successfully funded projects), the second (b) and third graph (c) give indication that the tax also leads to negative effects (decreasing sum and rate of successfully funded money). While a rising rate of successfully funded projects is good for project initiators, a decreasing amount of funded money is bad for platforms' revenues. Moreover, funders profit less from crowdfunding as the tax becomes some kind of transaction cost that is a hurdle to transactions, i.e., funding contributions. As a consequence, neither a tax of zero nor a high tax can be seen as an optimum.

(a) rate of succ. funded projects (b) sum of succ. funded money (c) rate of succ. funded money.

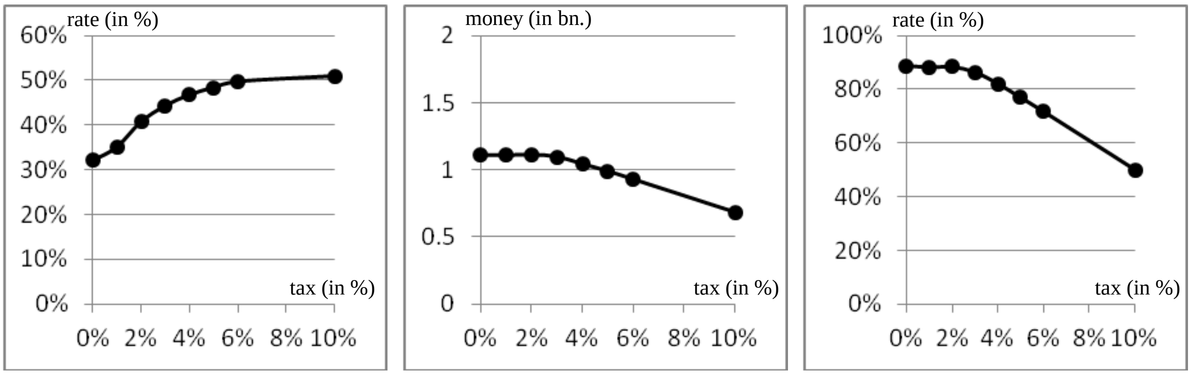

Figure 2. Resulting graphs considering different tax levels.

4 Discussion and Outlook

The rising rate of successfully funded projects in Figure 2 (a) seems to compensate for an only slight decrease of funded money in Figure 2 (b) in the area of taxes between 1% and 3%. We see that the rate of successfully funded projects (a) starts to level off after a certain amount of tax. Thus, the sensitivity analysis confirms that further increasing the tax does not help to reach much higher success rates. This can be explained mainly by the negative effect on funding activities. In case of taxes, there is an effect that reduces funding activity because a certain number of funders will refuse to spend the higher amounts for the rewards. For very high taxes which start to eliminate overfunding completely, the rate of successfully funded projects will even decrease again because less tax yield is available for redistribution. Nevertheless, low taxes do not have a great negative impact on funding activity. However, with an increasing tax, more and more funders will stop funding the project. As a platform's revenue is directly linked to the sum of funded money, higher taxes also ultimately mean lower revenues for the platform as the sum of successfully funded money decreases (b). As opposed to this negative effect, we expect an important positive effect for platforms: Higher rates of successfully funded projects (a) is likely to attract additional project initiators. In turn, funders are attracted because of a well-diversified portfolio of projects on the platform. Finally, the overall effect from a tax might even be positive for the platform operators, which redeems the lower sum of funded money (b).

The introduction of a tax could have another positive effect that does not become obvious directly from this analysis. Some funders might wait with their funding and observe the project for some time. However, in case of a tax that is applied as soon as the funding goal is reached, the funders may decide earlier to fund in order to avoid the additional costs. This effect would reduce funding hesitation at least if the project is close to its funding goal. This effect counters the bystander effect which is discussed in crowdfunding research (Kuppuswamy and Bayus, 2013). It would be a further important effect that supports projects which are close to their goal to finally reach it.

The results of the sensitivity analysis show strong support for introducing a tax for optimizing the overall funding results. We show that for certain tax levels the rate of successfully funded projects considerably increases. Nevertheless, the results also indicate that the tax level needs to be selected carefully, since the sum and rate of successfully funded money decreases with a higher tax. In order to find the optimal tax level, an evaluation formula is needed to counterbalance the negative and positive effects of the tax. Applying such evaluation functions, the optimal tax can be calculated from simulation outcomes and the ABM could be used as a decision support tool. For our analysis, we use data of a real online platform for initializing and parameterizing. In the given setup, the decision-making behavior is modeled without specific information about funders' price sensitivity. The proposed model is extendable and allows for considering such information. This would enhance the model to find an optimal level of tax for a certain crowdfunding system. The inclusion of this information, however, means no fundamental change in the methodology but leads to adjustments in the decision behavior.

Research on individuals' funding behavior has unveiled several interesting effects. The inclusion of all these effects is far beyond the scope of this paper. However, we are able to show that the method of funding decision behavior applied in our model is able to embrace such effects. The introduction of other effects is at the liberty of further research and of practitioners aiming to investigate the system for specific purposes. Finally, we point out that our model takes an on-platform perspective. Definitely, there are also questions that need a model of the complete market for platforms – in order to, for example, analyze a possible effect of migration (e.g., of funders or initiators) that takes place because of modifications of the funding model on a platform. However, we leave this perspective for further research. Moreover, our main focus is on reward-based crowdfunding. For other types of crowdfunding (e.g., crowdlending), we advise to consider further specific characteristics and data.

5 Conclusion

Although research has engaged with funding outcomes of campaigns and with several phenomena of individuals' funding behavior, interestingly, research literature concerning the quality or optimization of overall funding results is utterly scarce. Moreover, while researchers regularly use data from platforms or conduct surveys, research methods concerning simulations are almost completely neglected. The lack of simulation-based research in the field of crowdfunding as well as the missing research on the question of how the overall results derived through crowdfunding could be analyzed or even enhanced constitute a perfect fit. Therefore, we propose an agent-based model that considers individuals' funding behavior and well succeeds in achieving the characteristic funding distributions.

The contribution of this paper is twofold. Firstly, the paper contributes to the crowdfunding literature by discussing how crowdfunding serves best all of its stakeholders. Following the ideas of market engineering, we propose a taxation mechanism to internalize overfunding externalities and apply an agent-based model in order to evaluate our mechanism by means of sensitivity analysis. Thereby, we transfer the economic theory of internalizing externalities to the landscape of crowdfunding. Our results show strong support for applying our mechanism, since the rate of successfully funded projects increases while the sum of successfully funded money only slightly decreases for certain tax levels. In this sense, we deliver an interesting example of market engineering in the field of online crowdfunding platforms. Secondly, this paper gives a comprehensible outline of how to develop ABMs in the field of crowdfunding and gives insights into the design decisions. In previous research, we only find rudimentary decision-making using pure random variables. The decision-making behavior of agents seemed to be a big hurdle for developing crowdfunding ABMs that are more realistic. To address this gap, we engage with proposing a well-founded approach using the OWA operator and the MADM method. Thereby, we contribute to ABM modeling techniques and propose how decision behavior could be modeled. Of course, simplifications are needed and a system's complexity can only be reduced applying reasonable simplifications. Nevertheless, we advise to carefully regard possible effects of decision-making that might be important to certain scenarios or specific questions of interest. We address researchers and practitioners alike and invite research to further consider this powerful way of gaining new insights and to enhance the crowdfunding models applied.

References

Acharya, V. V., L. H. Pedersen, T. Philippon and M. Richardson (2010). "A Tax on Systemic Risk." In: *Proceedings of the Post-crisis regulatory reforms to secure financial stability: 2010 KDI international conference*, pp. 3–39.

Agrawal, A., C. Catalini and A. Goldfarb (2015). "Crowdfunding. Geography, Social Networks, and the Timing of Investment Decisions." In: *Journal of Economics & Management Strategy* 24 (2), 253–274.

Aidt, T. S. (1998). "Political internalization of economic externalities and environmental policy." In: *Journal of public economics* 69 (1), 1–16.

Alaei, S., A. Malekian and M. Mostagir (2016). "A Dynamic Model of Crowdfunding." In: *ACM Conference*. Ed. by V. Conitzer, D. Bergemann, Y. Chen. Maastricht: Netherlands.

Allison, T. H., B. C. Davis, J. C. Short and J. W. Webb (2014). "Crowdfunding in a Prosocial Microlending Environment. Examining the Role of Intrinsic Versus Extrinsic Cues." In: *Entrepreneurship Theory and Practice* 39 (1), 53–73.

Ballot, G., A. Mandel and A. Vignes (2015). "Agent-based modeling and economic theory. Where do we stand?" In: *Journal of Economic Interaction and Coordination* 10 (2), 199–220.

Barbi, M. and M. Bigelli (2015). "Crowdfunding Practices In and Outside the US." In: *Working Paper* (Version: 2015/03/12).

Baumol, W. J. and W. E. Oates (1971). "The Use of Standards and Prices for Protection of the Environment." In: *The Swedish journal of economics* 73 (1), 42–54.

Beaulieu, T., S. Sarker and S. Sarker (2015). "A Conceptual Framework for Understanding Crowdfunding." In: *Communications of the Association for Information Systems* 37, 1–31.

Bonabeau, E. (2002). "Agent-based modeling: methods and techniques for simulating human systems." In: *Proceedings of the National Academy of Sciences of the United States of America* 99 (3), 7280–7287.

Buchanan, J. M. and W. C. Stubblebine (1962). "Externality." In: *Economica* 29 (116), 371–384.

Burtch, G. (2011). "Herding Behavior as a Network Externality." In: *Proceedings of the Thirty Second International Conference on Information Systems (ICIS'11)*. Shanghai: China.

Burtch, G. and J. Chan (2014). "Reducing Medical Bankruptcy Through Crowdfunding. Evidence from GiveForward." In: *Proceedings of the Thirty Fifth International Conference on Information Systems (ECIS'14)*. Auckland: New Zealand.

Burtch, G., A. Ghose and S. Wattal (2014). "Cultural Differences and Geography as Determinants of Online Pro-Social Lending." In: *MIS Quarterly* 38 (3), 773–794.

Burtch, G., A. Ghose and S. Wattal (2015). "The Hidden Cost of Accommodating Crowdfunder Privacy Preferences. A Randomized Field Experiment." In: *Management Science* 61 (5), 949–962.

Chang, J.-W. (2016). "The Economics of Crowdfunding." In: *Working Paper* (Version: 2016/08/30).

Cholakova, M. and B. Clarysse (2015). "Does the Possibility to Make Equity Investments in Crowdfunding Projects Crowd Out Reward-Based Investments?" In: *Entrepreneurship Theory and Practice* 39 (1), 145–172.

Coase, R. H. (1960). "The Problem of Social Cost." In: *The Journal of Law and Economics* 3, 1–44.

Dahlman, C. J. (1979). "The Problem of Externality." In: *The Journal of Law and Economics* 22 (1), 141–162.

Dijkman, R. M., B. Sprenkels, T. Peeters and A. Janssen (2015). "Business models for the Internet of Things." In: *International Journal of Information Management* 35 (6), 672–678.

Doshi, A. (2014). "The Impact of High Performance Outliers on Two-Sided Platforms: Evidence from Crowdfunding." In: *Working Paper* (Version: 2014/10/20).

Fullér, R. (1996). "Exploring the limits of support systems." In: *Exploring the Limits of Support Systems*. Ed. by C. Carlsson, pp. 85–104: TUCS General Publications.

Gerber, E. M., J. S. Hui and P.-Y. Kuo (2012). "Crowdfunding. Why People Are Motivated to Post and Fund Projects on Crowdfunding Platforms." In: *Proceedings of the International Workshop on Design, Influence, and Social Technologies: Techniques, Impacts and Ethics*. Seattle (WA): US.

Gomber, P., J.-A. Koch and M. Siering (2017). "Digital Finance and FinTech. Current Research and Future Research Directions." In: *Journal of Business Economics* 87 (5), 537–580.

Grimm, V., U. Berger, F. Bastiansen, S. Eliassen, V. Ginot, J. Giske, J. Goss-Custard, T. Grand, S. K. Heinz, G. Huse, A. Huth, J. U. Jepsen, C. Jørgensen, W. M. Mooij, B. Müller, G. Pe'er, C. Piou, S. F. Railsback, A. M. Robbins, M. M. Robbins, E. Rossmanith, N. Rüger, E. Strand, S. Souissi, R. A. Stillman, R. Vabø, U. Visser and D. L. DeAngelis (2006). "A standard protocol for describing individual-based and agent-based models." In: *Ecological Modelling* 198 (1-2), 115–126.

Gupta, A. K. and A. Prakash (1993). “On Internalization of Externalities.” In: *Working Paper* (No. 1126).

Kim, J., M. Lee, D. Cho and B. Lee (2016). “Are All Spillovers Created Equal? The Impact of Blockbusters and the Composition of Backers in Online Crowdfunding.” In: *Proceedings of the Thirty Seventh International Conference on Information Systems (ICIS'16)*. Dublin: Ireland.

Koch, J.-A. (2016). “The Phenomenon of Project Overfunding on Online Crowdfunding Platforms. Analyzing the Drivers of Overfunding.” In: *Proceedings of the Twenty-Fourth European Conference on Information Systems (ECIS'16)*. İstanbul: Turkey.

Koch, J.-A. (2017). “A Framework for the Notion of 'Utility' in the Landscape of Crowdfunding.” In: *Proceedings of the Twenty-Fifth European Conference on Information Systems (ECIS'17)*. Guimarães: Portugal.

Koch, J.-A. and Q. Cheng (2016). “The Role of Qualitative Success Factors in the Analysis of Crowdfunding Success. Evidence from Kickstarter.” In: *Proceedings of the 20th Pacific Asia Conference on Information Systems (PACIS'16)*. Chiayi: Taiwan.

Koch, J.-A. and M. Siering (2015). “Crowdfunding Success Factors. The Characteristics of Successfully Funded Projects on Crowdfunding Platforms.” In: *Proceedings of the Twenty-Third European Conference on Information Systems (ECIS'15)*. Münster: Germany.

Kuppuswamy, V. and B. L. Bayus (2013). “Crowdfunding Creative Ideas. The Dynamics of Project Backers in Kickstarter.” In: *Working Paper* (Version: 2013/03/16).

Lee, Y.-C., C.-H. Yen and W.-T. Fu (2016). “Improving Donation Distribution for Crowdfunding. An Agent-Based Model.” In: *Proceedings of the 9th International Conference on Social, Cultural, and Behavioral Modeling*. Washington (DC): USA.

Li, Z. and J. A. Duan (2014). “Dynamic Strategies for Successful Online Crowdfunding.” In: *Working Paper* (Version: 2014/09).

Liu, J., L. Yang, Z. Wang and J. Hahn (2015). “Winner Takes All? The "Blockbuster Effect" in Crowdfunding Platforms.” In: *Proceedings of the Thirty Sixth International Conference on Information Systems (ICIS'15)*. Fort Worth: USA.

Lu, C.-T., S. Xie, X. Kong and P. S. Yu (2014). “Inferring the Impacts of Social Media on Crowdfunding.” In: *the 7th ACM international conference*. Ed. by B. Carterette, F. Diaz, C. Castillo, D. Metzler. New York (NY): USA, pp. 573–582.

Macal, C. M. and M. J. North (2010). “Tutorial on agent-based modelling and simulation.” In: *Journal of Simulation* 4, 151–162.

Malave, I. (2012). “Why Kickstarter Should More Fully Integrate Social Media.” In: *Working Paper* (Version: 2012/11).

Mollick, E. (2014). “The dynamics of crowdfunding. An exploratory study.” In: *Journal of Business Venturing* 29 (1), 1–16.

Neumann, D., J. Maekioe and C. Weinhardt (2005). “CAME - A Tool Set for Configuring Electronic Markets.” In: *Proceedings of the Thirteenth European Conference on Information Systems (ECIS'05)*. Regensburg: Germany.

Nikolic, I. and A. Ghorbani (2011). “A method for developing agent-based models of socio-technical systems.” In: *International Conference on Networking, Sensing and Control (ICNSC'11)*. Delft: Netherlands, pp. 44–49.

Pigou, A. C. (1920). *The Economics of Welfare*. London, UK: MacMillan and Co., Limited.

Pitschner, S. and S. Pitschner-Finn (2014). “Non-profit differentials in crowd-based financing. Evidence from 50,000 campaigns.” In: *Economics Letters* 123 (3), 391–394.

Timmers, P. (1998). “Business Models for Electronic Markets.” In: *Electronic Markets* 8 (2), 3–8.

Weinhardt, C., C. Holtmann and D. Neumann (2003). “Market-Engineering.” In: *Wirtschaftsinformatik* 45 (6), 635–640.

Williamson, O. E. (1971). “The Vertical Integration of Production. Market Failure Considerations.” In: *The American Economic Review* 61 (2), 112–123.

Xu, Z. (2015). *Uncertain Multi-Attribute Decision Making*. Heidelberg, Germany: Springer.

Yager, R. R. (1988). “On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decisionmaking.” In: *IEEE Transactions on Systems, Man, and Cybernetics* 18 (1), 183–190.

Yang, Y., H. J. Wang and G. Wang (2016). “Understanding Crowdfunding Processes. A Dynamic Evaluation and Simulation Approach.” In: *Journal of Electronic Commerce Research* 17 (1), 47–64.

Zhang, J. and P. Liu (2012). “Rational Herding in Microloan Markets.” In: *Management Science* 58 (5), 892–912.

Zvilichovsky, D., Y. Inbar and O. Barzilay (2015). “Playing Both Sides of the Market. Success and Reciprocity on Crowdfunding Platforms.” In: *Working Paper* (Version: 2015/09).