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Andreas Savov

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1 Introduction

In recent years, crowdfunding has received increased attention and reputation as an alternative investment method (Belleflamme et al., 2014, p. 585). Through online crowdfunding platforms, entrepreneurs, also described as founders in the context of crowdfunding, can address a crowd of internet users and ask for financial support of their campaign. As it is known from popular successful campaigns, the "Pebble" smartwatch for instance, crowdfunded projects can accumulate substantial amounts of money. The relevance of crowdfunding is further emphasized by governmental initiatives focusing on crowdfunding, such as regulations and information campaigns (Kuppuswamy and Bayus, 2015, p. 2). However, besides the increasing popularity and relevance of crowdfunding, it is also important to point out that successful crowdfunding campaigns are not common.

The majority of crowdfunding campaigns actually does not receive sufficient funding (Mollick, 2014, p. 6). Successful projects, however, can result in innovative products which sometimes even make the news and quite often would not have received sufficient funding otherwise. If the majority of campaigns fail, how can founders appeal to potential contributors and convince them to invest money? Specifically, how can unique characteristics of crowdfunding be used efficiently to improve coordination between market participants and make a campaign a success?

Crowdfunding differs from traditional investment methods in several regards. First and foremost, instead of relying on an institution or a small number of professional investors, a crowdfunding campaign aims to initiate a collective effort of financial support (Belleflamme et al., 2014, p. 586). Secondly, the communication between entrepreneurs and contributors on crowdfunding platforms ensures that involvement by contributors is not limited to money but can include feedback and suggestions as well (Ellman and Hurkens, 2016, p. 42). Furthermore, successful crowdfunding campaigns can include the possibility of acquiring funds which exceed the required investment. Additionally, incentives in crowdfunding can be monetary as well as non-monetary. Non-monetary incentives, also described as rewards, are one of the most interesting features of crowdfunding since they allow founders to address consumers rather than investors to fund their campaigns.

These special properties of crowdfunding, however, do not lead to the success of a campaign if they are not used efficiently. The goal of this thesis is to empirically analyze elements of crowdfunding campaigns and to examine, how they can be utilized to coordinate contributions efficiently. Especially the effects of rewards and their prices on success are analyzed to better understand the role of incentives in crowdfunding. Furthermore, the effects of campaign elements on collecting funds beyond the required sum, a funding behavior which is called "overfunding", is examined.

The structure of this thesis is divided into nine sections. The first section aims to provide a general overview of crowdfunding and the motivations of participants. Section 2 focuses on the model of Kickstarter, one of the largest reward-based crowdfunding platforms. Within this section, Kickstarter's campaign elements and terms of use are explained. In section 3, the focus is placed on the role of rewards in crowdfunding. The importance of overfunding for crowdfunding campaigns is explained within section 4. In section 5, hypothesis are formulated to explain the effects of incentives on success probabilities and overfunding. An overview of the data is provided in section 6 of the paper. Parts 1 and 2 of section 7 explain the econometric model used to examine the effects of campaign elements on the probability of success and presents the results. The third part of section 7 includes a description of the econometric model and the fourth part includes the corresponding results to examine the effects of campaign elements on the level of overfunding.

Section 8 compares the elements of specific campaigns with the implications of the main findings. The final section, section 9, summarizes the main findings.

1.1 An Overview of Crowdfunding

Before we can take a closer look at the participants in crowdfunding, it is important to get an overview of crowdfunding. The first part of the section presents a general definition of crowdfunding while the second part of the section describes the different models used on crowdfunding platforms. The purpose of this section is to explain the similarities and differences between crowdfunding models. Moreover, this section explains why the reward-based model is especially suited to explain the potential of crowdfunding to improve coordination between market participants.

Crowdfunding is a rather ambiguous description of a multitude of financing models using crowd dynamics. A refined definition from Belleflamme et al. (2014, p. 588) explains: *"Crowdfunding involves an open call, mostly through the Internet, for the provision of financial resources either in the form of donation or in exchange for the future product or some form of reward to support initiatives for specific purposes"*.

Crowdfunding platforms are a subcategory of multi-sided markets. In previous research by Rochet and Tirole (2003, p. 990), two sided markets were characterized by the presence of two distinguishable sides who benefit from interaction through a common platform. Crowdfunding does not necessarily require the infrastructure of the internet, but it is safe to assume that it would not have become as popular as it is today without the communication features of the internet and its social features (Belleflamme et al., 2014, p. 587). Another reason for its popularity is the option to choose from different crowdfunding models.

Mollick (2014, p. 3) differentiates between four predominant crowdfunding models, the patronage model, the lending-based model, the reward-based model and the equity-based model. These crowdfunding models differ in the motivation of the contributors to support a campaign, the type of compensation and the group of contributors. The following part of this section provides a brief explanation of the models.

The patronage model, also called donation-based model, is used especially to realize artistic and humanitarian projects. It is quite similar to charity, but instead of direct donations a crowdfunding platform is used to facilitate the collection and transfer of donations. Donors are driven by altruistic motives and do not expect any direct compensation for their financial contribution. Since the primary purpose of donation-based campaigns is charity, they are not relevant in the context of this thesis. Consequently, we focus on other crowdfunding models which are not based on altruistic motivation.

In contrast to the donation-based model, financial contributors in lending-based models do expect a rate of return on their investment. The equity-based model is similar to the lending-based model since contributors expect financial returns, but instead of a return rate, equity investors expect equity stakes and voting rights as a compensation for their investment. This form of crowdfunding is highly regulated (Mollick, 2014, p. 3), for instance by the J.O.B.S act[1] (Jumpstart Our Business Startups Act) passed by President Obama in April 2012.

In the reward-based model, contributors, who are also described as backers in the context of crowdfunding, pledge their financial support to a campaign in order to receive non-monetary compensations, also called "rewards". This model is quite different from the other models in several aspects. The differences are described in table 1:

[1] "Jumpstart Our Business Startups" Act, https://www.sec.gov/spotlight/jobs-act.shtml

CROWDFUNDING MODELS

MODEL	MOTIVATION	COMPENSATION	CONTRIBUTORS
REWARD BASED CROWDFUNDING	EGOISTIC	NON-MONETARY	CONSUMERS
EQUITY BASED CROWDFUNDING	EGOISTIC	MONETARY	INVESTORS
LENDING BASED CROWDFUNDING	EGOISTIC	MONETARY	INVESTORS
DONATION BASED CROWDFUNDING	ALTRUISTIC	NO COMPENSATION	DONORS

Table 1: An overview of crowdfunding models.

When comparing it to the donation-based model in which backers are motivated by altruism, backers of reward-based crowdfunding campaigns expect compensation although this compensation takes the form of non-monetary rewards instead of return rates or shares. Considering the motivations of backers, the reward-based model is more similar to the equity-based model and the lending-based model. The major differences between the reward-based model and these two models however are the differences in incentives on one hand and the addressed group of contributors on the other hand.

While backers in equity-based models and lending-based models are motivated primarily by their expected financial compensation and are not necessarily interested in the final product of the crowdfunded campaign, backers in reward-based models are generally interested in the final product of a campaign and essentially are potential consumers who become investors (Ordanini et al., 2011, p. 3). This specific property of the reward-based model to improve coordination between producers and consumers is one of the reasons why this model is very important in the context of this thesis. Additionally, the reward-based model allows founders to gain access to funding at lower costs than in equity models and lending models (Agrawal et al., 2014, p. 70). Since this study analyzes data from the reward-based platform Kickstarter[2], the remaining part of this thesis will focus on the reward-based model.

The decision to focus on reward-based crowdfunding comes at a loss of generalizability. According to previous research, motivations of backers who participate in reward-based, equity-based and lending-based campaigns are similar (Agrawal et al., 2014, p. 73). Nevertheless, the differences between individual campaigns regarding presentation and project characteristics make success of reward-based campaigns more dependent on heterogeneous preferences of backers when compared to equity-based and lending-based campaigns (Belleflamme et al., 2015, p. 14). Furthermore, differences between crowdfunding models regarding their regulation and campaign structures limit comparability across platforms (Mollick, 2014, p. 13).

Considering the purpose of reward-based crowdfunding, the efficient outcome of a campaign is the realization of a specific project conditional on sufficient support from its backers. Therefore, coordination between participants in crowdfunding campaigns describes the efficient allocation of funds conditional on the attributes of the project and the preferences of the supporters (Yen et al., 2017, p. 248).

Despite the differences in campaign goals and relationships of participants, crowdfunding

[2] https://www.kickstarter.com

models share the principle of facilitating coordination between founders and backers to realize projects. The reward-based model is especially interesting in this context since founders in this model call out to consumers instead of investors to contribute. The next section will explain the motivations of participants in reward-based crowdfunding in more detail.

1.2 Motivations of Participants in Reward-Based Campaigns

In order to understand the coordination and interactions of participants in crowdfunding campaigns on Kickstarter, this section describes the motivations of participants in reward-based crowdfunding.

The following graph (figure 1) provides an initial overview of the interactions between participants in reward-based crowdfunding campaigns:

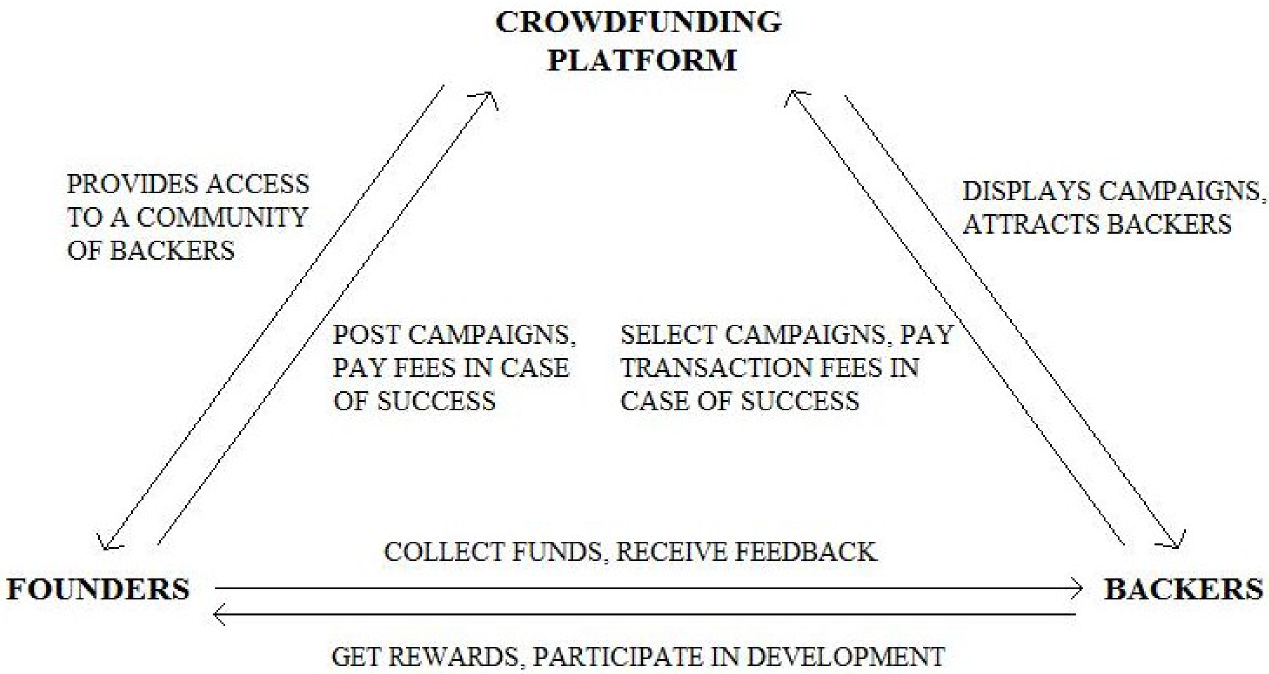

Figure 1: Interactions between participants in reward-based crowdfunding.
(Based on Haas et al., 2014, p. 13, figure 3)

Campaign founders are quite often entrepreneurs who find themselves in a tough spot. They need money to start their venture, but it is difficult for them to convince people to invest at an early funding stage. Reward-based crowdfunding offers a possible solution to this problem because it enables founders to access funding at reduced costs.

Rewards might not be attractive for conventional early stage investors, but backers of crowdfunding campaigns hold memorabilia of their favorite soon-to-be-released products in high esteem. Essentially they appreciate these items of affection so much that they pledge money to a campaign. These rewards enable founders to display their creativity. They include anything from production stills for movie projects to signed prototypes to early access for video games. Since incentives play a major role in reward-based crowdfunding, they are further explained in section 3 of this thesis.

However, without a good project which offers attractive rewards presented in an informative way such that backers experience the gratification of participation and value the project enough to pledge money to it, this method of financing is less likely to appeal to backers and thus might become an unfeasible funding method if the founder is ill prepared. So even if the costs are reduced, founders do not get financial support for free.

A founder needs to spend a great deal of time and effort to design a successful campaign and to manage communications through the crowdfunding platforms' website as well as other social networks (Agrawal et al., 2014, p. 76). Furthermore, she needs to convince backers why her project deserves funding more than other projects, and she needs to think about setting a threshold goal which is high enough to cover minimal costs, but not high enough to scare off backers. The goal setting strategy becomes even more relevant considering the possibility of overfunding as explained in section 4 of this thesis.

Aside from the reduced cost of funds, the ability to test for demand is a unique feature of "all-or-nothing" crowdfunding platforms which may drive founders to choose this specific crowdfunding model over other means of financing. The "Pebble" Kickstarter campaign is an example to illustrate the difference in information quality between traditional early-stage investors and a crowd of backers (Agrawal et al., 2014, p. 71) . Although the creator, Eric Migicovsky, got discouraged by traditional early-stage investors, the feedback on Kickstarter was very positive and exposed sufficient demand for production. The support for Pebble through pledges and coverage on social networks provided capital while at the same time reducing the costs of capital from traditional sources of funding. This example demonstrates how entrepreneurs can utilize crowdfunding platforms to test for demand of a product. However, the support of backers is not merely restricted to financial contributions.

A crowd of backers can offer support beyond pledges and advertisement in social networks. By participation during the development phase of a product, interested consumers assume a testing function and provide additional input and quality assurance to improve the product. Regarding the Pebble project, the addition of Bluetooth 4.0 compatibility after backers requested this feature exemplifies this phenomenon (Agrawal et al., 2014, p. 72).

After explaining the incentives for campaign founders to use crowdfunding as a financing method, it is also necessary to explain why campaign backers are willing to financially support crowdfunding campaigns on Kickstarter even if they do not get any financial returns at all.

While in a conventional market customers pay for products, this is not necessarily true for Kickstarter campaigns. Depending on the campaign and its individualized rewards, backers might indeed pledge money to finance a project and simultaneously acquire the product as a reward similar to pre-order goods, but in other cases rewards might not include the actual product. In other words, the commodity sold is not generally a product, but rather the existence of a product and a reward. These rewards can include anything from a mention on a "Thank You" Screen to exclusive offers at expensive levels (Crosetto and Regner, 2014, p. 11). The influence of a campaign's rewards on its success greatly depends on how supporters of a campaign relate to it, how much they identify themselves with the project and how immersed they feel.

One might argue that it is unlikely for backers to benefit from campaign success if founders are inexperienced and fail to deliver on their promises. This poses the question whether campaign success is truly advantageous for backers. However, since unsuccessful campaigns tend to miss their goals by large amounts, it is assumed that backers are able to recognize high-quality projects (Mollick, 2014, p.6).

In contrast to rewards, crowdfunding offers other less tangible benefits to campaign backers. These benefits are also present in social networks and communities. Participants who value a project get to experience it and are able to interact with other enthusiasts and the project's creators themselves (Agrawal et al., 2014, p. 73). The value they get from participation in a campaign depends on the campaign's design. Campaign creators may reward backers who advertise their projects on social media platforms or contribute otherwise in several ways. A campaign's success is not only important for founders and backers, but for the crowdfunding platform as well.

Project creators need a platform to promote their campaigns, and these crowdfunding platforms are autonomous market participants with their own incentives and motivations. Similar to the situation in other two sided markets, crowdfunding platform owners are faced with the "chicken-and-egg problem", the challenge to balance both sides in the market (Rochet and Tirole, 2003, p. 990). To solve this problem, crowdfunding platforms employ a specific price structure of the provided service in order to balance the number of backers and founders.

Considering the price structure of major reward-based crowdfunding platforms, founders are treated as the profit-making segment and backers are treated as loss leader. Platforms such as Indiegogo[3] and Kickstarter, for instance, earn revenue by charging fees for successful projects and payment fees (Cumming et al., 2014, p. 7). Therefore it is in Kickstarter's own interest to host as many successful projects as possible.

Crowdfunding platforms can be understood as an extension of social networks. They are similar regarding their dependence on a big community, and in order to utilize network effects to attract a big community, crowdfunding platforms need to appeal to as many project creators as possible while at the same time they need to uphold their reputation of hosting appealing projects. These "showcase projects" improve media coverage to reach even more founders and backers.

Summarizing the main drivers for participants of crowdfunding, each distinctive group has different reasons to become involved. While backers primarily react to incentives and additionally value the opportunity of a community experience, founders are able to access funds at lower cost and to connect with backers who are interested not just in providing financial support but also feedback and advertisement in social media. The crowdfunding platform intends to attract backers by hosting successful campaigns on one hand. On the other hand, it wants to attract founders who present interesting projects which have the potential to attract more backers. Success matters for all participants involved for the following reasons.

Because of the "aon" model, founders only receive funds if the campaign goal is reached which means that they cannot realize their projects in case of failure. Backers pledge to a campaign because they are interested in the rewards and the final outcome of a campaign. The availability of both features depends on the success of a campaign. Finally, crowdfunding platforms profit from successful campaigns since they can only charge transaction fees to backers and campaign fees to founders if a campaign reaches its funding goal.

[3] https://www.indiegogo.com

2 Kickstarter's Crowdfunding Model

In this chapter of the thesis, the specific properties of the "all-or-nothing" (aon) model used on Kickstarter are explained. Additionally, advantages and disadvantages of the "aon" model regarding risk, quality of campaign description and motivation of backers are explained by comparing it to the "keep-it-all" (kia) model. Finally, the most important stages of a Kickstarter campaign and their meaning for the success of a campaign are described.

Since crowdfunding describes several different crowdsourced financing models, we need to discuss how the platform funding scheme itself can reduce risks. Reward-based crowdfunding platforms offer two different funding schemes. The focus of this thesis is on the "aon" funding scheme as it is used on Kickstarter. The second reward-based funding scheme is the "keep it all" (kia) funding scheme which is used in the context of this thesis merely as a contrast to the "aon" funding scheme in order to compare features between reward-based crowdfunding models and emphasize unique features of the "aon" funding scheme. Regarding the motivation of backers, both schemes offer non-monetary compensation in the form of "rewards". Therefore, contrary to donation-based crowdfunding, backers of "aon"- and "kia" campaigns generally do not pledge money to campaigns due to altruistic motives (Steigenberger, 2017, p. 348). Furthermore, unlike in equity-based and lending-based campaigns, backers of reward-based "aon"- and "kia" campaigns are not investors because they do not receive financial compensation.

Even though online crowdfunding platforms are a relatively new phenomenon, Kickstarter's "all-or-nothing"-scheme has some history. It can be traced back to the provision point mechanism used to improve the private provision of public goods (Agrawal et al., 2014, p. 86; Hu, M., 2015, p. 333). This mechanism ensures that a public good is provided only under the condition that a previously set contribution goal is reached. If the goal is not reached, the funds are returned to the contributors. In the "aon" model, this mechanism is especially important to reduce the risk of underfinanced projects for backers (Cumming et al., 2014, p. 4).

While the "aon" model decreases the risk for backers, it increases the founder's risk since money pledged is only transferred in the event that the campaign goal is fully reached. For example, even if the campaign is relatively successful and reaches 80% of the funding goal, the founder receives no money at all. Simultaneously, the "aon"-model decreases risks for backers because, apart from goals which are set beneath the sum required by the founder to realize a project according to its description, the problem of underfunded campaigns is mitigated. The increased risks taken by founders when self-selecting into the "aon"-model motivate them to provide additional information on the campaign website to attract more backers and improve the success probabilities of their campaigns (Cumming et al., 2014, p. 12).

The "kia" model works in a different way. Founders can start production or a project even if the funding threshold hasn't been reached. While this is a feasible option for scalable products, it might increase the risk of deterioration in quality inherent with under-financed projects (Cumming et al., 2014, p. 11). Popular examples for scalable products are music-CDs, ebooks and video-games. Dependent on funds available for the production, costs can be cut by reducing the number of levels, graphics quality or other gameplay-features. Therefore they are adaptable to different levels of funding by adjustment of minimum production costs. While this model can reduce risks for the entrepreneur by providing utility even if the campaign goal hasn't been reached, it is less likely to achieve the funding goal (Cumming et al., 2014, p. 17).

Besides risk reduction, another feature of the "aon"-model is its motivational capacity to incentivize backers. As long as the campaign goal is not reached, production is not guaranteed. This means that contrary to the "kia"-model, potential backers cannot choose between funding a campaign and buying the product in the post-campaign market since the second option is only available if sufficient backers step in to fund the project in time.

Campaign founders who commit to starting a campaign on Kickstarter cannot solely rely on reaching enough backers during the campaign lifecycle, so usually they try to build up momentum by announcing their campaigns on social platforms, thus aggregating support before the actual start date. Previous research has shown that the first few days influence the success of a campaign significantly (Agrawal et al., 2014, p. 67; Belleflamme et al., 2015, p. 21). The number of early-stage backers and their willingness to pay more than the minimum pledge-level provides expert signals to casual backers, since it is generally known that initial backers put in more effort to collect information about campaigns and their success probabilities. The decision of backers to rely on the funding behavior of early-stage backers can result in steadily increasing funding patterns which are described as herding behavior. However, while herding patterns have been observed in equity-based and lending-based crowdfunding, reward-based crowdfunding campaigns on Kickstarter exhibited "bathtub" shaped funding patterns (Kuppuswamy and Bayus, 2015, p. 4).

At the start of a campaign, it is difficult to deduce success probabilities from the number of backers. Generally, if a promising campaign reaches the 50% threshold, crowd dynamics lead to additional funding (Mollick, 2014, p. 6). Regarding these funding dynamics, backers take the biggest risk at the start of the campaign lifecycle compared to other stages of the campaign, so in order to justify that risk, early stage backers are assumed to be well informed “expert backers” who deem a project potentially successful even at the start date. Consequently, their pledging behavior is interpreted as expert knowledge by casual backers and therefore closely observed.

Although we consider merely the start of the campaign, we can already recognize several factors which influence the decisions and actions of founders and backers during this initial stage: The campaign founder signals commitment to the project by choosing a platform with an “aon” model over a "kia" model. The level of detail of the project presentation on the Kickstarter platform is another tool to signal quality to potential backers. Last but not least, founders offer so-called "early bird" rewards which are only available for early backers in order to collect more pledges during the first days of a campaign.

Assuming that the campaign did not reach its campaign goal earlier, the end of the funding duration is another very important stage of the campaign. In contrast to the campaign start, success probabilities of a project are easier evaluated at this later stage of the campaign by looking at the amount of support in terms of funds and backers. Furthermore, while potential backers can wait during the campaign for other backers with a higher valuation to fund the project, their opportunity to contribute to the realization of the project of interest disappears at the end of the campaign (Kuppuswamy and Bayus, 2015, p. 17). The deadline effect coerces these careful backers into funding the campaign since the success of the campaign depends on their contribution.

In this section of the paper, the specific characteristics of Kickstarter's reward-based "aon"-model were explained. There are three major points in which Kickstarter's model is distinguishable from the reward-based "kia"- model: risk reduction, quality signaling by founders and motivation for backers. The "aon" funding scheme decreases the risk of underfinanced projects and increases chances of successful funding. Additionally, founders who self-select into the "aon" funding scheme to signal quality and commitment provide more information about their project than "kia" campaign founders. Regarding the campaign progression, the campaign start is very important and indicative of success probabilities of a campaign. Conditional on the possibility that the campaign did not reach its goal before its deadline, the end of the funding duration provides more incentives to contribute in the "aon" funding scheme than in the "kia" funding scheme since, contrary to the "kia" funding scheme, the realization of projects depends on crossing the threshold in the "aon" funding scheme.

Risk reduction is not just a very important issue in the "aon" model, but a very important issue in crowdfunding in general. For this reason, the following section explains the ways in which Kickstarter's terms of use aim to reduce risks.

2.1 Kickstarter's Terms of Use: an Overview

The crowdfunding platform Kickstarter acts as an intermediary between campaign founders and backers. In order to better understand the rules of the platform and their effects on founders and backers, it is important to discuss the terms of use from the Kickstarter website[4]. These terms of use contain several paragraphs about standard disclosures regarding account management, limitations of support, warranty, limitations of liability and copyright. Additionally, several paragraphs were included to reduce risks for backers and increase accountability for founders. In section 2 of this thesis, the risk resulting from underfinanced projects was identified as one of the major disadvantages of crowdfunding platforms. Other possible disadvantages of crowdfunding platforms include fraudulent activities of founders (Griffin, 2012, p. 391) and inexperienced backers (Griffin, 2012, p. 386; Hazen, 2012, p. 1766). Therefore it is important to analyze how the terms of use can counteract these shortcomings.

The major risk for backers of crowdfunding campaigns is the possibility that a campaign founder successfully promotes a campaign which reaches the funding goal, takes the money and runs. This is the quintessential moral hazard which might be relevant in the context of crowdfunding, but has not been a significant problem empirically (Mollick, 2014, p. 12). Furthermore, the terms of use enable legal action if founders do not fulfill their obligations.

Since fraud is not a common occurrence, the biggest risk from a backer's point of view is mismanagement of time, money, or both by founders. Considering that crowdfunding primarily attracts founders who are inexperienced, the probability of delayed delivery because of either financial miscalculation or increased demand is quite high. The terms of use notify backers of this risk and urge them to consider that even if founders are absolutely committed to fulfill their obligations, changes regarding delivery dates or reward specifications are quite common even though they happen unintentionally.

When crowds of people interact online, expectations collide and miscommunication becomes a risk. For this reason, rules are implemented to prevent disagreements between platform users. This section explained how Kickstarter's terms of use aim to increase trust by defining responsibilities and obligations of users. For instance, users should generally not break the law, lie or engage in fraudulent or deceptive behavior. Furthermore, even if Kickstarter as an intermediary cannot sue founders who fail to fulfill their obligations, backers can take legal action against founders since it constitutes a breach of contract.

However, since backers and founders are often amateurs and problems arise more frequently from lack of experience than from ill-intent, the terms of use include a disclaimer which explains the general risks involved with founding and backing a campaign, especially the risk of delays.

While the terms of use covered in this section described the legal framework of Kickstarter, the following section focuses on the campaign elements which provide the functionality framework on Kickstarter.

4 https://www.kickstarter.com/terms-of-use

2.2 Kickstarter Campaign Elements

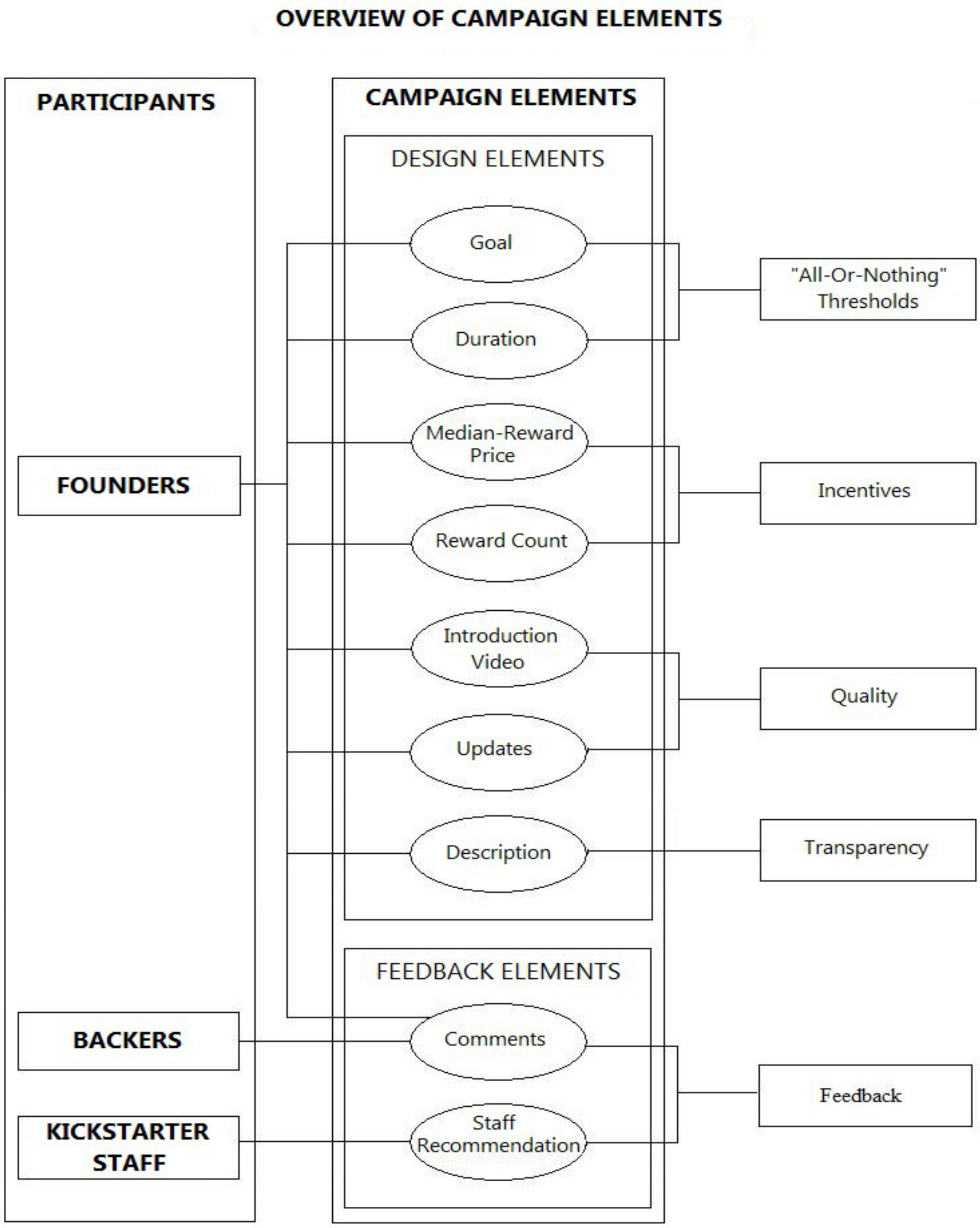

Figure 2: Classification of campaign elements.

To understand the ways in which founders can increase the success probability of their campaign by appealing to backers efficiently, it is important to explain the elements of a Kickstarter campaign. Founders who start a campaign on Kickstarter have to follow a predefined structure to present their projects. This structure consists of several elements which can be separated into two groups depending on the way in which founders can influence them. Elements which are used to present information about the campaign and offer a high level of customizability to founders can be described as "design elements", while elements with the main purpose to provide feedback and communication can be described as "feedback elements".

2.2.1 Design Elements

"All or Nothing" - Thresholds:

The "All or Nothing-thresholds" campaign elements are determined by the time- and money-dimension of the campaign. By adjusting these parameters, founders can inform backers about the amount of funds required to realize their projects as well as the available timeframe to reach the funding thresholds.

Goal: Even though founders start campaigns on Kickstarter for several other reasons such as feedback, publicity and demand testing, the prevalent reason is probably the acquisition of financial means to realize their projects. In the "aon"-model, the achievement of the funding goal is the final measure of campaign success. Therefore, the threshold goal requires special attention by the founder. Since the terms of use constitute that posting a campaign and receiving pledged money is as legally binding as a contract between founders and backers, founders need to ensure that the amount specified as a goal is sufficient to realize projects according to their description in case of success. This condition determines the lower limit of the range which is available for the goal value.

Regarding the upper limit of the range in which founders can set the goal, a lower value for the threshold goal is known to increase the probability of campaign success (Mollick, 2014, p. 8; Kuppuswamy and Bayus, 2015, p. 14). Consequently, founders should set their campaign goals as low as possible. However, setting the goal below the amount required to realize the project might result in Kickstarter not approving the campaign due to its unsound financial plan. Balancing development costs while simultaneously keeping the goal as low as possible restricts a founders freedom in choosing a threshold goal.

Contrary to the duration threshold of a campaign, the threshold goal does not automatically trigger the campaign end if the funding goal is reached. For instance, if a campaign with its duration set at 30 days reaches its goal within 10 days, potential backers still have the possibility to contribute until the end of the funding period. In such situations, campaigns can surpass their funding goals and reach different levels of overfunding, a funding behavior which will be more thoroughly explained in section 4.

Duration: Similar to the threshold goal, shorter campaign durations are known to increase the success probability of campaigns (Mollick, 2014, p. 8; Cumming et al., 2014, p. 22; Kuppuswamy and Bayus, 2015, p. 14). While the duration can assume any value from 1 to 60 days, Kickstarter recommends a maximum duration of 30 days since campaigns tend to lose momentum if they exceed this limit. On the other hand, without previous community building efforts in social networks during the pre-funding phase, a shorter duration increases the risk of the campaign not reaching as many potential backers as possible.

Incentives:

In reward-based crowdfunding, non-monetary incentives provide the main motivation for backers to contribute to campaigns besides altruistic motives. Depending on the characteristics of the project, founders can offer rewards which relate to the project in different ways. The number of different rewards depends on content and scalability of a project. A larger number of different reward categories provides an increased diversification of incentives for backers and is more likely to appeal to a larger group of backers by satisfying heterogeneous preferences (An et al., 2014, p. 4; Kunz et al., 2016, p. 475).

While some rewards may include the final outcome of the project, more expensive rewards frequently offer options for personalization and premium features. Cheaper rewards may be scaled down versions of the campaign's final product or other product-related accessories. Compared to other campaign elements, incentives offer an increased level of individual customizability and can be specifically adjusted to a campaign's specific characteristics such as category, scope, funding goal and final product. Therefore, the reward structure and -pricing is very dependent on the campaign and will be further discussed in section 3 of this thesis.

Quality:

Usually, the first time backers discover a campaign, they are unaware of a founders personality and skillset. Even though campaign-related information provided on the Kickstarter platform is a first step to become acquainted with a project, the founder still remains an unknown person. For this reason, founders' efforts to present themselves to their backers and to inform the community of backers about their campaign progress are interpreted as signs of quality.

Introduction Video: Kickstarter advises every founder to post an introduction video since a lack thereof decreases success probability of a campaign. First impressions can be important, and an introduction video on top of the campaign site provides more information than an image. Besides being informative, a good introduction video signals commitment by the founder to reach her funding goal since she put in the effort to produce it. It also helps backers to get a better impression of how a founder wants to present her project. Previous research has proven the effect of an introduction video on success probabilities (Mollick, 2014, p. 8; Kuppuswamy and Bayus, 2015, p. 14).

Quickupdate: Updates are the most efficient method for founders to inform all backers simultaneously about recent campaign activities, development progress and other campaign features such as the announcement of stretch goals. Since the first few days of a campaign are very important for the success of a project, an update within the first 3 days can be interpreted as a sign of commitment on the founder's site (Mollick, 2014, p. 8) and furthermore as community building effort. Contrary to comments which are posted by founders and backers, updates are posted exclusively by founders.

Transparency:

***Description*:** Backers who visit a campaign website for the first time probably try to get an idea of the project by watching the introduction video, but once they decide that the campaign might be worth pledging money to, their attention shifts to the description of the campaign. This part of the campaign site serves several purposes. The primary purpose is information in general, but the description also specifies the project features which the founder needs to provide if the collected amount of pledges reaches the threshold goal. Considering this function of the description, a longer description is assumed to increase transparency and to build trust between backers and founders (Crosetto and Regner, 2014, p. 10; Kunz et al., 2016, p. 470).

2.2.2 Feedback Elements

After discussing the design elements, it is also interesting to take a closer look at feedback elements. These elements are for the most part beyond a founders' direct control. This means that founders depend on other participants to make these elements work in their favor.

Comments: While updates are relevant for existing and new backers alike, comments primarily address existing backers to exchange thoughts about the project and react to updates (Cumming et al., 2014, p. 8, Mollick, 2014, p. 6). Similar to updates, comments demonstrate the founder's commitment to interact with her community, but they also demonstrate backers' motivation to participate in the development of the project.

Staff Recommendation: Contrary to design elements, founders have no direct influence on the recommendation status of their campaign. It is up to Kickstarter's staff members to decide whether they deem a project to be recommendable or not. Certain factors such as a solid presentation and sufficient variety in rewards are assumed to improve chances of recommendation according to Kickstarter, but partially the deciding factors which lead to a recommendation are based on individual preferences and therefore not generally known. From a strategic point of view, it is in Kickstarter's best interest to promote projects which are close to achieving their funding goal since Kickstarter only profits if a campaign is successful (Belleflamme et al., 2015, p. 16). For example, a project which achieved 80% of its funding goal within three weeks of a four-week campaign duration may very well depend on a recommendation in order to pass its funding threshold in the remaining time. According to the data set used in this thesis, the majority of campaigns which cross the 50%-funding threshold are successful, but projects which lose momentum during the second half of the campaign can greatly benefit from additional support generated by a recommendation. Conclusively, a recommendation is assumed to work as a catalyst to increase the overall number of successful projects. This effect has been observed in previous research (Kuppuswamy and Bayus, 2015, p. 14; Mollick, 2014, p. 8).

Kickstarter offers a framework to enable creators to design campaigns individually. However, at the same time creators are expected to abide by a specific structure when presenting their project. Campaign elements within this structure offer different levels of customizability for founders. Feedback elements offer the lowest flexibility in that regard since they depend on the reactions of other participants to the project while design elements allow for more customization options. Within these design elements, incentives present founders with the opportunity to choose the rewards they want to sell to their backers, the level of diversification they want to provide and the price they set according to their expectation of demands. To further elaborate on how founders can optimally adjust rewards corresponding to individual campaign features, the following section will explain them in more detail.

3 Rewards

Contrary to equity-based and lending-based crowdfunding campaigns, backers of Kickstarter campaigns are not entitled to shares of revenues or return rates from successful campaigns. Considering this uniqueness of rewards, it is interesting to examine non-monetary incentives and their effects in reward-based crowdfunding more closely.

Reward-based crowdfunding can be compared to donation-based crowdfunding and equity-based crowdfunding in terms of total funding volume. While lending-based crowdfunding demonstrates the largest share of funds in figure 3, it is important to mention that according to the source of the graphic (http://crowdexpert.com/crowdfunding-industry-statistics/), the funds accounted for from lending-based platforms were not restricted to lending-based crowdfunding platforms, but lending-based platforms in general. However, disregarding the broad definition of lending-based crowdfunding for the moment, it is safe to say that the total volume of funds collected in reward-based crowdfunding is comparable to the total volume of funds collected in donation-based crowdfunding and equity-based crowdfunding.

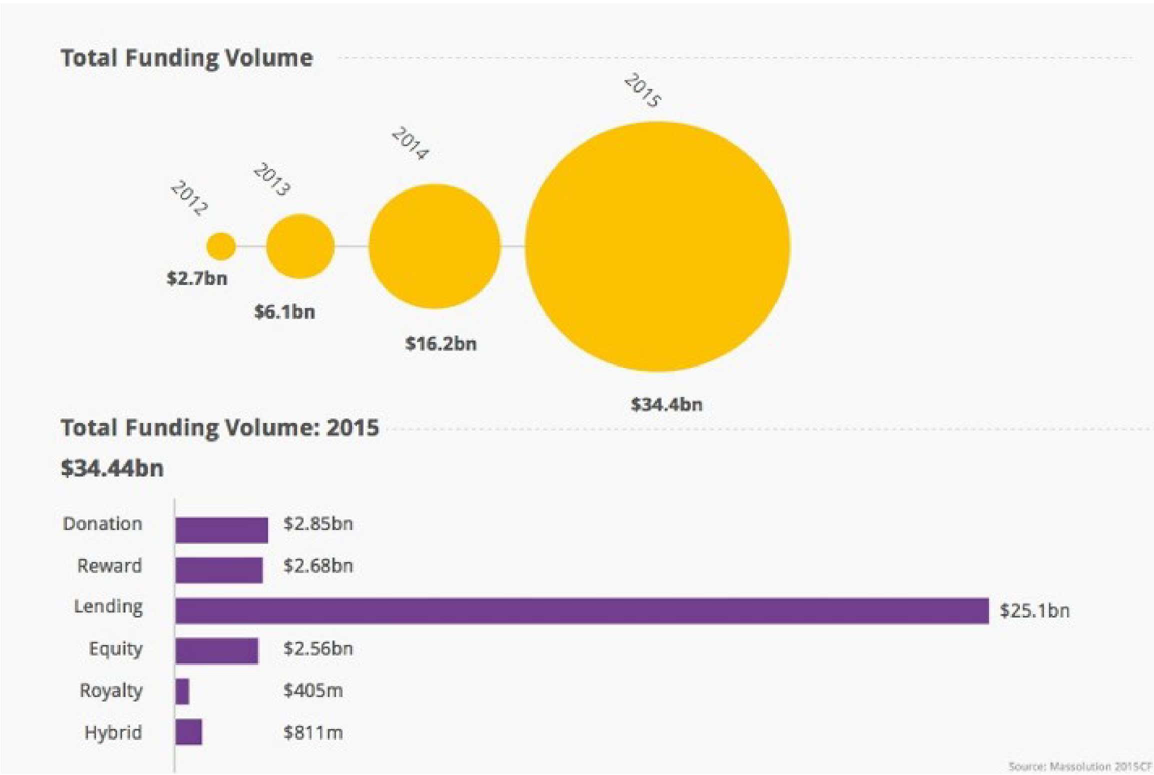

Figure 3: Growth by crowdfunding model prediction for 2015 in millions of USD (research based estimate)
Source: *http://crowdexpert.com/crowdfunding-industry-statistics/ ; Massolution Crowdfunding Report 2015*

While reward-based crowdfunding platforms are similar regarding the compensation of contributions in form of non-monetary rewards, they can still differ from each other considering their rules, campaign categories and other platform-specific attributes. Figure 4 displays the relative share of traffic (views per month) of the 20 biggest crowdfunding platforms for the period between February 2015 and February 2017, regardless of crowdfunding model. Besides the two reward-based crowdfunding platforms Patreon[5] and Indiegogo, and the donation-based platform GoFundMe[6], Kickstarter is among the most popular crowdfunding platforms.

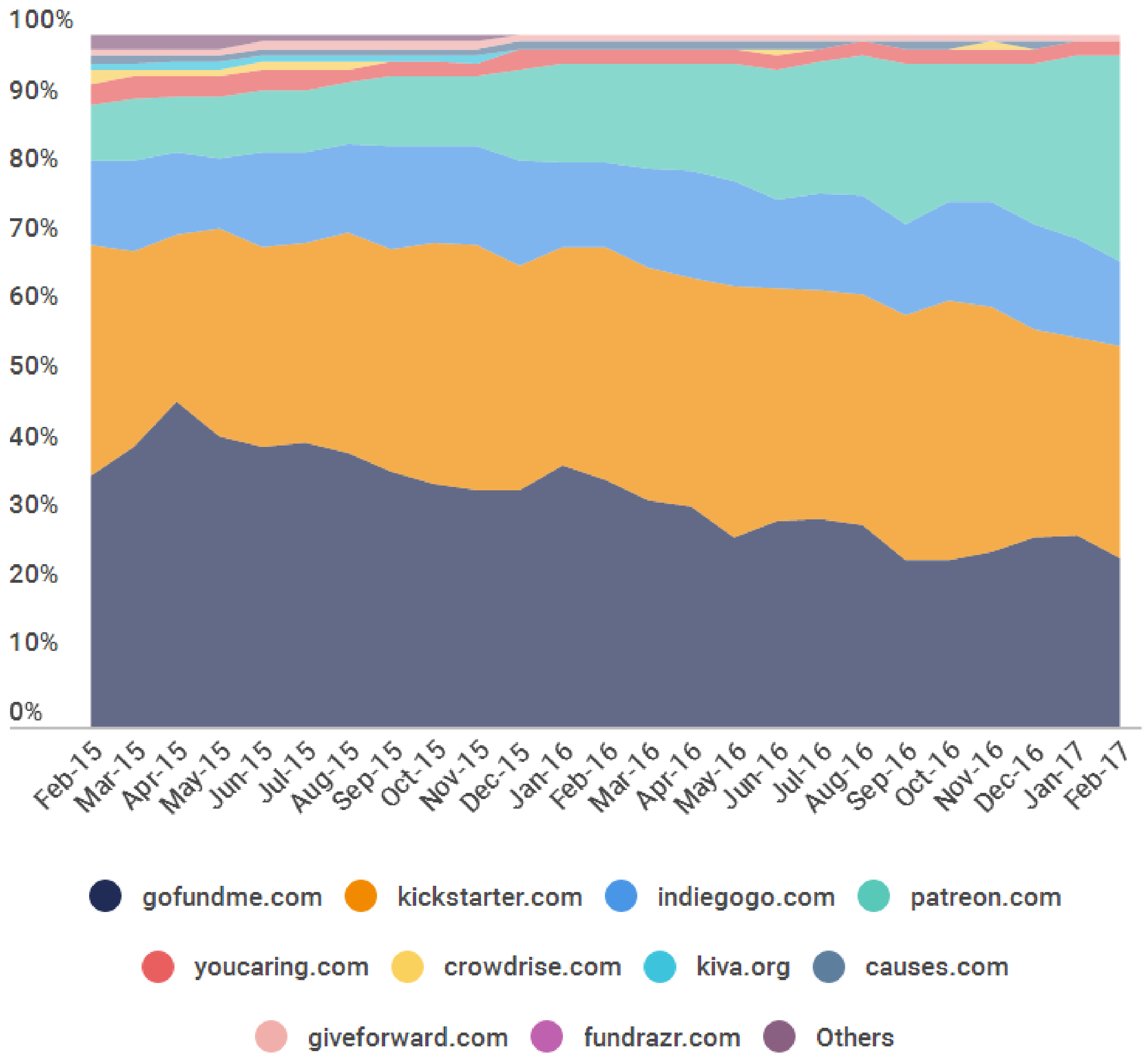

Figure 4: Relative traffic-share (views per month) of the 20 biggest crowdfunding platforms.
Source: *https://www.similarweb.com/blog/digital-marketing-strategies-for-crowdfunding*

To get a better idea of Kickstarter's share of reward-based crowdfunding, Figure 5 shows the total amounts of funds collected for the three most popular reward-based crowdfunding platforms. As of February 23rd, 2017, Kickstarter held the largest share of total amounts collected (72,7%) when compared with other major reward-based crowdfunding platforms such as Indiegogo (26%) and Patreon (1,3%).

5 https://www.patreon.com/
6 https://www.gofundme.com/

	Indiegogo	Kickstarter	Patreon
Amount Raised/pledged	Over $1 billion raised	$2.8 billion pledged	$50 million raised

Figure 5: Total amounts raised as of February 23rd, 2017 for the three largest reward-based crowdfunding platforms. Source: *https://fitsmallbusiness.com/best-crowdfunding-site/#stats*

Since Kickstarter is the largest reward-based crowdfunding platform in terms of total amounts raised and one of the largest crowdfunding platforms considering its web traffic, using data from Kickstarter provides the possibility to analyze a very large share of the crowdfunding-market.

On Kickstarter, backers can support projects in several ways. They can contribute an amount of their choice without receiving any compensation at all, or they can pledge an amount which equals the price of a reward. In the first case, backers contribute to the project without expecting any compensation. In previous research papers, behavior of this kind has been explained by several factors including warm-glow and community participation (Ellman and Hurkens, 2016, p. 36; Andreoni, 1990, p. 464). Warm-glow describes an altruistic motivation to participate in a community experience without considering compensation. The reward for the contributor is the experience itself, but it has been shown that this effect is stronger for humanitarian and artistic projects. Incidentally, reward-based crowdfunding is sometimes described as an evolution of the patron-model (Kuppuswamy and Bayus, 2015, p. 2), a model which enables artists to get funded directly by their followers.

On Kickstarter, rewards are the major motivation for backers to pledge money to a project. Depending on the project, rewards can include anything from a photo of a movie set to a signed edition of a comic. In some cases, rewards provide exclusive access to pre-order the final product of a campaign. If the project is for example a cookbook, creators can provide rewards such as a signed pre-order copy of the book, a personal video message or special cooking dishes mentioned in the book. However, compared to a movie project, they will not be able to provide a dinner with actors as a reward because there were probably no actors involved in the production of the book in the first place. This example demonstrates how the characteristics of a project determine creators' possibilities to provide rewards.

It also means that, the more developed the underlying concept of a project is, the more substance it provides for the creation of rewards related to the project. Rewards essentially compensate backers for their financial contributions by giving them the opportunity to experience the production process closer than anyone else. Considering the concept of their project, founders set the number of different rewards, reward prices and reward limits at the campaign start. For founders, these reward structures serve two purposes (Ellman and Hurkens, 2016, p. 44). Firstly, apart from the total number of backers, they provide additional information about the demand for a project to the campaign founder. Secondly, these rewards are a tool to increase funding by taking the preferences of backers into consideration. According to previous research, campaigns which offer more distinctive reward categories are more successful.

The main difference between buyers' decisions in conventional markets and backers' decisions in crowdfunding campaigns depends on the availability of the product (Hu et al., 2015, p. 331). If the production of a good is secured, a buyer will try to maximize her utility according to her preferences and pay the smallest price possible. In crowdfunding, the backer contributes to increase the probability of campaign success. Despite the fact that a higher reward level might offer only a marginal difference in utility, the increased success probability of the campaign is valued by the backer. In other words, pledging more money to get a higher reward might increase utility for the backer even if the reward itself provides no additional value at all.

The results of Hu et al. (2015, p. 336) show that the profits from menu pricing strategies can surpass profits from uniform pricing strategies under the condition that there are fewer high-type buyers who have a high valuation and the difference in valuation between high-type and low-type buyers is sufficiently large. This affects social welfare since the founder is able to appeal to more buyers which leads to an increase in total surplus. The authors also consider the simultaneous case. If all backers contribute at the same time, the menu pricing dominates other strategies for a larger parameter space (Hu et al., 2015, Appendix p. 3). This means that the menu pricing is preferable for more variations of high-type and low-type buyers. Ellman and Hurkens (2016, p. 39) arrive at similar results. Their model describes only a simultaneous contribution process since they argue that pledges can be canceled and changed before threshold goals or deadlines are reached.

In behavioral economics, several influences on backers' decisions for choosing reward levels are explained. One of them is the middle option bias, a preference to choose moderate options of a choice set over extreme options (Valenzuela and Raghubir, 2009, p. 4). Backers who intend pledging to a campaign in order to receive a reward face the following trade-off. On one hand, they want to profit from their participation and contribution to the campaign by claiming some special memorabilia. On the other hand, they are generally not interested in the most expensive rewards which are usually designed to appeal especially to die-hard fans of a campaign. Results from previous research have shown that backers of crowdfunding campaigns are prone to the middle option bias (Simons et al., p. 8).

In order to measure the effect of middle option reward prices on success probabilities of campaigns, two measures come to mind: the average price and the median price. The following example, a fictional movie project, will demonstrate the effect of different pricing structures on these measures:

Campaign Example: Movie Project 1

Rewardnumber	Description	Price (USD)
1	"Thank You"- postcard	10 $
2	DVD-Copy	25 $
3	Signed Limited Edition	35 $
4	Ultimate Edition	45 $
5	Premiere Ticket	80 $
6	V.I.P. Premiere Ticket	90 $
	Mean Reward Price:	**47,5 $**
	Median Reward Price:	**40 $**

Table 2: Price structure example 1.

In this first example, the founder offers six different reward levels ranging from 10$ to 90$. The two mid-level rewards are available at 35$ and 45$ respectively while the most expensive reward level is priced at 90$. When comparing the mean-reward price to the median-reward price, the mean-reward price is higher since the number of reward levels is relatively low and the difference in price between the higher reward-levels and the mean-reward price is bigger than the difference in price between the lower reward-levels and the mean-reward price.

Considering the middle option bias, the median-reward price is better suited to describe the mid-level rewards compared to the mean-reward price. In the following example, the reward structure includes three additional high-priced rewards:

Campaign Example: Movie Project 2

Rewardnumber	Description	Price (USD)
1	"Thank You"- postcard	10 $
2	DVD-Copy	25 $
3	Signed Limited Edition	35 $
4	Ultimate Edition	45 $
5	Premiere Ticket, Date 1	80 $
6	Premiere Ticket, Date 2	80 $
7	Premiere Ticket, Date 3	80 $
8	Premiere Ticket, Date 4	80 $
9	V.I.P. Premiere Ticket	90 $
	Mean Reward Price:	**58,33 $**
	Median Reward Price:	**80 $**

Table 3: Price structure example 2.

Compared to campaign example 1, the mean-reward price increased only by a small amount. At the same time, however, the median-reward price increased by 40$. This large increase can be explained by the increased diversification in high-priced rewards which pushed a higher-priced reward into the middle section of the reward structure. Considering the positive effect of an increased middle option bias on pledges, the second campaign is assumed to be more successful than the first.

Besides non-monetary incentives, another unique property of crowdfunding compared to other forms of investment is the possibility of campaigns to exceed their set funding goals, a practice which is called "overfunding". If a campaign collects more than the requested amount, founders have the opportunity to set additional funding goals which are described as "stretch goals". The specifics of overfunding and the relevance of stretch goals within overfunding will be the main focus of the following section 4.

4 Overfunding and Stretch Goals

Overfunding describes a situation in which backers pledge sufficient money not just to reach the campaign goal, but to surpass it. Depending on the campaign strategy of the founder, overfunding can have different effects. While some founders use additional funds to increase the quality of their rewards and to add additional rewards, other founders use them to extend their projects by defining additional funding goals, also described as "stretch goals". Scalable projects for instance, especially projects with the purpose of developing digital products, can include stretch goals to extend their product features conditional on the additional amounts of money received.

For example, considering a music-CD, the stretch goals could be structured in the following way. Successful completion of the campaign results in the base product with ten songs. However, the campaign does not simply end after reaching its goal if the deadline is not reached. Additional goals provide additional incentives for backers to pledge to a campaign. In the context of the music-CD example, a stretch goal at 120% of funds achieved could provide two additional songs, while another stretch goal at 130% results in an additional CD-case cover to choose from.

This stretch goal strategy can be viewed as a collective reward system, and it changes the funding dynamics of the campaign in several ways. First and foremost, it provides additional incentives for backers even after campaign success. Secondly, additional product features which get enabled by overfunding are only accessible after campaign success. This means that stretch goals provide an incentive for backers to pledge to a campaign not only after its successful completion, but even during the regular campaign. Furthermore, stretch goals keep a campaign alive after its success. Without them, backers would still be able to pledge to a campaign, but there would be no specified increase in utility after it achieved its funding goal. Previous research has shown that campaigns which offer stretch goals exceed their threshold goals by a larger amount than campaigns without stretch goals (Li and Jarvenpaa, 2015, p. 14)

Regarding the effects of stretch goals, backers pledge to a project with the intention of realizing additional product features. Even if the campaign is already successful, they have an incentive to contribute. For instance, considering the example of the music-CD described previously, if we assume that a backer is compelled to hear the two additional songs, it is evident that she could not achieve the same satisfaction by simply pledging to another project. Moreover, the campaign for the music-CD has already been successful, therefore, assuming that the first stretch goal is reached, the possibility of listening to the bonus songs is larger than listening to any other unfinished music-CD campaign.

However, considering the more general case of a project without stretch goals, the effect of overfunding is more complex. In this context, it is important to discuss the meaning of a threshold goal. The goal of a campaign serves several purposes. First and foremost, it provides information about development costs to backers. Regarding this information, backers can compare the costs of development to the value of the final product and form an opinion about the feasibility of the campaign and its probability of success. Furthermore, the purposing of funds provides additional insight into what backers can expect from the project. A sound financial plan can persuade backers of the founder's management skills and experience while the lack of financial planning raises doubts about the success probability.

Without overfunding, founders would fully depend on the amount of funds set as goal to cover their costs. Assuming this dependence, it is rational for them to set the goal equal to the production costs even if a large goal caused by high production costs decreases probability of success (Mollick, 2014, p. 8; Kuppuswamy and Bayus, 2015, p. 14). The implementation of overfunding affects founders' incentives to set the goal at least as high as the production costs. According to previous research (Gabison, 2016, p. 503), founders prefer to set the goal below the production costs in the "aon"-model. The deadline effect of this model distorts incentives in a way that founders choose to risk a successful underfunded campaign over an unsuccessful campaign which failed because its true goal was not reached. In this way, they can increase the success probability of their project since they are not confined by the amount of funds collected from achieving the threshold goal.

The extent of the negative effect on project quality caused by a low goal is unclear. Underfinancing of successful campaigns leads to an increase in the likelihood of delayed deliveries (Mollick, 2014, p. 13), but even if a backer assumes that a campaign's goal is set too low, she might still pledge to it. Depending on her preferences, she might value a reward with late delivery higher than missing out on it altogether. Furthermore, the campaign progress severely influences backers' decisions. If the backer despises delayed deliveries, she has the option to fund other campaigns which yet have to achieve success.

One critique of overfunding in the "aon"-model is that backers pledge to successful projects instead of supporting projects which have not reached their goals yet (Gabison, 2016, p. 502). This argument suggests however that backers have equal preferences across campaigns. Coming back to the music-CD example which describes a successful campaign with a goal set above production costs, in the worst case scenario a backer receives the CD with ten songs. If the stretch goals are reached, she gets the additional utility of up to two songs. Backing another music campaign which is not yet successful instead would not increase her utility.

5 Hypothesis

The goal of this thesis is to examine how crowdfunding can improve coordination between market participants. In order to determine the effects of campaign elements on coordination, the effects of Kickstarter campaign-elements on the efficient allocation of funds will be examined by analyzing their effect on campaign success and overfunding. When compared to traditional forms of investment, non-monetary incentives and overfunding are unique features of crowdfunding campaigns, therefore, special focus will be put on rewards and stretch goals.

Previous empirical research by Mollick (2014) measured the effect of Kickstarter's campaign elements on success probabilities. The empirical analysis in this thesis builds on his work in several aspects. Since the data set used in this thesis contains campaigns from Kickstarter similar to the data set used by Mollick, the campaigns follow the same structure. Consequently, campaign elements which were examined in his research were also included in this thesis due to identical campaign structures. However, due to the focus on incentives in this thesis, additional campaign elements were included.

One of these additional campaign elements is the reward count, a number which describes the number of different reward categories and can be interpreted as a measure of incentive diversification. Previous research (An et al., 2014, p. 4; Kunz et al., 2016, p. 475). found that an increase in reward categories has a positive effect on success probabilities of campaigns. Therefore, it is assumed that additional reward categories in Kickstarter campaigns also improve success probabilities of campaigns:

H.1.1.: Rewards are the main motivation for backers to pledge money to reward-based crowdfunding campaigns. A larger number of distinctive reward-categories improves the probability of campaign success.

Besides the number of rewards, the median reward level has been added to analyze the effect of the reward price structure on incentives. Simons et al. (2017) analyzed the effect of middle option rewards on success probabilities in crowdfunding. They concluded that backers preferred the middle option regardless of the price range and the number of different prices. Based on these results, an increased price of the median reward level is assumed to have a positive effect on success probabilities:

H.1.2.: The price of the median level reward has a positive effect on campaign success. Since most backers choose mid-level rewards rather than minimum or maximum-level rewards, an increase in prices for mid-level rewards has a positive effect on campaign success.

Before a campaign has reached its funding goal, rewards are the most important incentives to pledge money to a campaign. However, after a campaign reaches its funding goal, backers have the opportunity to pledge money to the campaign until the designated deadline of the campaign is reached. During this period, additional community incentives called "stretch goals" can be reached. Stretch goals are not mandatory campaign elements of a Kickstarter campaign which means that not every campaign offers stretch goals in the event of success.

Previous research (Li and Jarvenpaa, 2015) found that stretch goals have a positive effect on overfunding. According to these findings, it is assumed that the presence of stretch goals increases the amount of overfunding.

H.2.: Similar to rewards, stretch goals provide specific incentives for backers to contribute to a campaign even after the funding threshold has been reached. In this way, stretch goals are a measure of utility gained by backers from increased overfunding. Therefore, campaigns which provide stretch goals are expected to achieve higher levels of overfunding than campaigns without stretch goals.

6 Data Description

The data set used in this thesis is a cross-sectional sample of 50.315 projects from the crowd-berkeley crowdfunding database[7], a data collection provided by the Kauffman foundation and the Fung institute, for which data about comments, rewards and updates were available. This data was combined with data about campaign recommendations from the "webrobots.io" webscraping service[8]. The following table describes the data merging and -filtering process:

Dataset	Observations	Procedure
Crowd Berkeley Kickstarter Data	298.054	Delete if live, suspended or canceled
	264.996	Delete if currency is not US-Dollar
	218.860	Filter goal >= 4000 USD
	131.664	Delete if no backers
Crowd Berkeley KS Update-Data	117.356	Merge data-sets
Crowd Berkeley KS Reward-Data	117.285	Merge data-sets
Webrobot Kickstarter Data	116.768	Merge data-sets
	63.718	Delete if neither failed nor successful
	63.046	Delete if missing *quickupdate*
	62.971	Delete if missing *backers*
	62.269	Filter categories
Final Sample:	50.315	

Table 4: Data merging and -filtering steps.

7 https://crowdfunding.haas.berkeley.edu/wp
8 https://webrobots.io/kickstarter-datasets

6.1 Data Set H.1

Categories which included less than 10 observations for cross-tabulations of dummy variables were excluded to avoid any problems resulting from zero-cells in logistic regression. Projects with funding goals below 4000 dollars were excluded from the study since they did not represent significant amounts of money in absolute terms. Furthermore, only projects with funding goals denoted in US-Dollars were included to avoid any problems caused by currency conversion. Similar to previous research (Kuppuswamy and Bayus, 2015, p. 10), projects which attracted no backers at all were excluded from the study since they did not represent a serious effort to attract pledges.

The categories which contained sufficient observations according to the previously mentioned criteria (art, design, film & video, games, music, publishing and technology) are described in table 5. The table displays the mean and the standard deviation for all campaigns, for successful campaigns and for campaigns within each included category. The following categories did not contain sufficient observations in the sample based on these criteria and were therefore excluded from the sample: comics, crafts, dance, fashion, food, journalism, photography and theater.

Summary Statistics H.1

	All	Successful	Art	Design	Film & Video	Games	Music	Publishing	Technology
rewardcount	10.19	12.06	9.319	10.42	11.40	11.39	10.68	9.248	7.916
	(6.448)	(6.769)	(6.569)	(6.218)	(6.846)	(6.870)	(6.318)	(5.987)	(5.125)
medianrewardprice	154.7	139.6	174.6	147.5	175.4	102.5	137.8	113.2	212.1
	(369.0)	(173.4)	(453.4)	(311.2)	(337.4)	(213.5)	(243.4)	(269.5)	(614.3
goal	56160.9	19320.3	43493.9	60435.9	79291.8	65116.4	19903.6	18915.2	105143.5
	(1127312.4)	(50886.1)	(950284.6)	(1458603.4)	(1394464.1)	(1396283.3)	(438891.4)	(301498.2)	(1486979.5)
duration	35.44	34.24	35.59	35.35	35.78	32.75	36.53	34.66	35.93
	(12.18)	(11.28)	(13.46)	(10.06)	(13.00)	(9.605)	(13.21)	(11.40)	(11.14)
amountpledged	26112.5	47277.8	6343.2	90574.2	16879.2	69851.5	7719.9	8081.3	40377.2
	(195858.5)	(267908.3)	(22126.8)	(578892.4)	(88017.1)	(319704.2)	(15264.2)	(22573.4)	(181845.2)
ratiofunded	1.131	2.060	0.591	3.331	0.751	2.550	0.775	0.695	1.129
	(5.322)	(7.208)	(1.144)	(8.344)	(0.686)	(14.01)	(0.660)	(1.248)	(4.171)
updates	8.35	14.03	4.85	12.43	8.66	19.01	5.92	6.70	5.78
	(12.04)	(13.87)	(8.052)	(11.21)	(10.82)	(21.50)	(7.375)	(9.660)	(9.491)
comments	124.0	231.6	4.4	135.8	19.1	933.9	6.3	7.3	76.7
	(2481.7)	(3413.9)	(22.63)	(686.4)	(582.5)	(7549.1)	(48.99)	(33.86)	(492.7)
bodylength	3332.5	3863.5	2702.1	3699.8	3502.6	5158.0	2211.5	3298.5	3632.0
	(3128.3)	(3103.5)	(2316.5)	(2932.9)	(2832.0)	(4184.4)	(1819.9)	(3784.7)	(3294.1)
N	50315	26494	4597	3032	12489	5239	10566	7102	7290

mean coefficients; sd in parentheses

Table 5: Summary Statistics of the Sample for H.1.

When we look at the funding goals, technology campaigns and campaigns within the "film & video" category have the highest goal on average. Game campaigns receive the most comments on average followed by campaigns within the technology category.

Regarding effects of incentives, founders of movie- and game campaigns offer the largest number of different rewards on average. Backers of technology campaigns have to contribute the highest amount on average for a median reward, followed by backers of movie campaigns.

Figure 6 describes the number of successful and failed projects for each category included in the sample. It shows that the proportion of successful campaigns and failed campaigns greatly differs between categories. For instance, the design category exhibits the largest proportion of successful campaigns while the technology category exhibits the smallest proportion of successful campaigns. Therefore it is necessary to control for differences in success probabilities between categories in the regression-models.

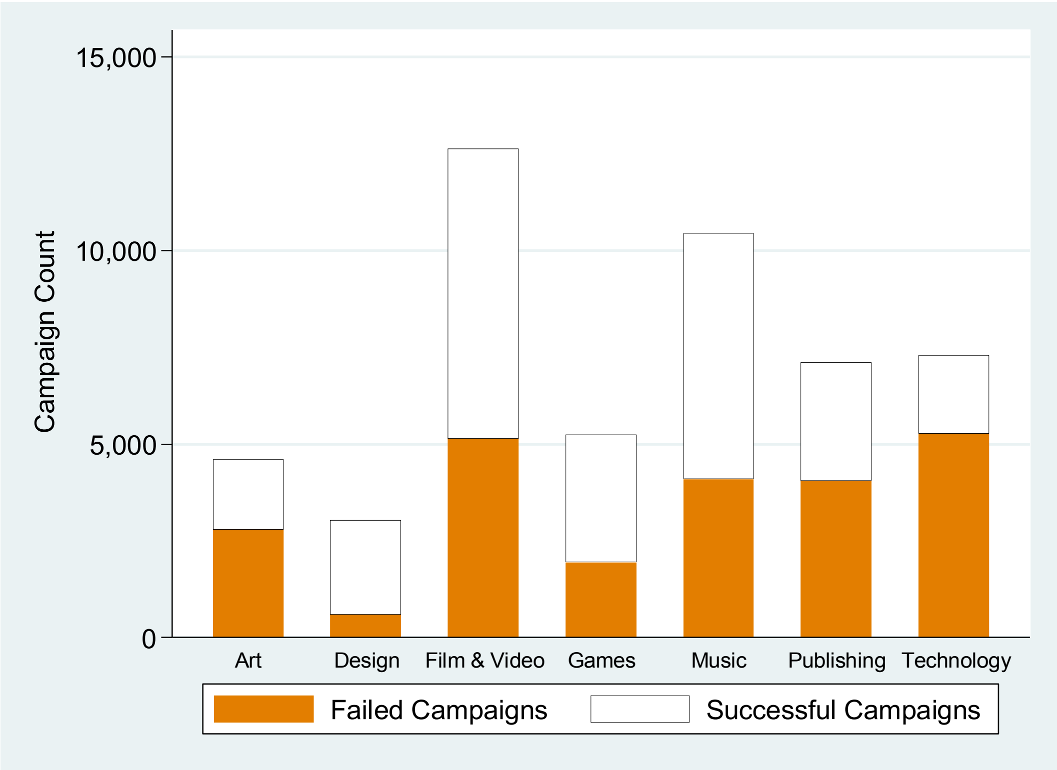

Figure 6: Proportion of successful campaigns and failed campaigns per category.

Figure 7 shows that campaigns rarely fail if they pass the 50% funding threshold for several reasons. To understand the underlying decision mechanisms, it is important to analyze the signaling effect of currently accumulated funds on potential backers during the campaign cycle. At the campaign start, supporters who are interested in a campaign primarily have to rely on the information provided on the campaign page. As the campaign progresses, reactions to the campaign by community members provide additional information on the success probabilities of the campaign. The data suggests however that herding effects are not sufficient to raise funds above the 50% threshold if projects are of low quality. This observation concurs with previous research by Mollick (2014, p. 6). Furthermore, it means that backers can distinguish between projects of high quality and projects of low quality.

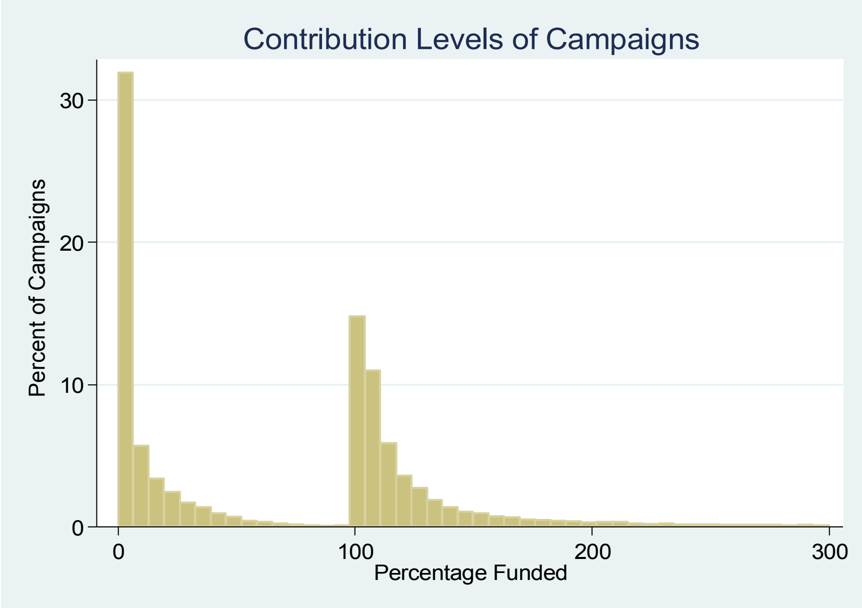

Figure 7: Histogram of Funding Levels.

6.2 Data Set H.2

In order to test for effects of campaign characteristics on overfunding, the data set used for H.1 was modified in the following ways. Since the focus for the second model is to test how campaign characteristics can influence moderate levels of overfunding, only campaigns which received between 105 % and 150 % of their funding goals were included in the sample. Furthermore, considering extreme values of the comments variable, campaigns which showed either zero comments or a number of comments larger than 708 were excluded from the sample. Summary statistics for the comments variable are presented in table 6:

comments

	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	12,457
25%	1	0	Sum of Wgt.	12,457
50%	5		Mean	68.63932
		Largest	Std. Dev.	1453.106
75%	17	24932		
90%	64	31428	Variance	2111517
95%	144	32069	Skewness	84.01539
99%	708	145925	Kurtosis	8200.886

Table 6: Summary statistics of *comments* for overfunded campaigns.

10.389 observations remained in the final sample for model 2. A descriptive summary of key variables sorted by categories is provided in the appendix. Regarding the levels of overfunding, higher levels of overfunding occur less frequently than lower levels of overfunding. Figure 8 describes the difference in levels of overfunding for campaigns which exceeded their funding goals by 5 % -50%:

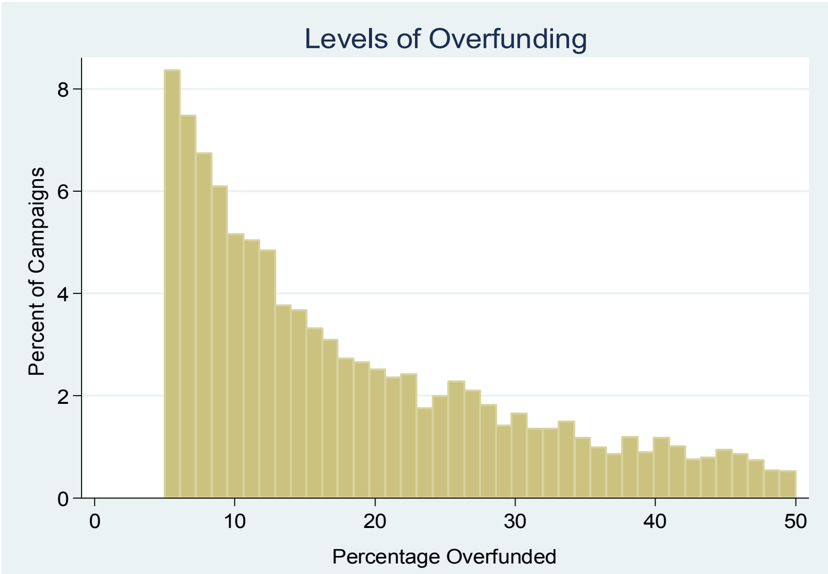

Figure 8: Histogram of overfunding levels.

7 Models and Results

7.1 Econometric Model H.1

The structuring of the reward system in terms of the number of different reward-types and pricing of rewards is assumed to significantly affect the success probability of a campaign. The purpose of the first econometric model in this thesis is to test the effects of the following reward-specific design attributes on campaign success:

H.1.1.: Rewards are the main motivation for backers to pledge money to reward-based crowdfunding campaigns. A larger number of distinctive reward-categories improves the probability of campaign success.

H.1.2.: The price of the median level reward has a positive effect on campaign success. Since most backers choose mid-level rewards rather than minimum or maximum-level rewards, an increase in prices for mid-level rewards has a positive effect on campaign success.

The logit model was used because of the binary response variable *stateid* which can take two possible values to describe the success or failure of a campaign. Since the logit model has the advantage that results can be presented as odds-ratios, the logit model was chosen over the probit model. The econometric model H.1 builds on previous research by Mollick (2014, p. 5) which was one of the first empirical studies of the Kickstarter platform. In his research, Mollick introduced a method to measure the effects of campaign elements on success odds. The following formula describes the logit model to test H.1.1 and H.1.2:

$$P(Y=1)=1/(1+[exp(-1*[\beta_0+\beta_1 rewardcount+\beta_2 medianrewardprice+\beta_3 loggoal+ \beta_4 duration+\beta_5 introvid_d+\beta_6 quickupdate_d+\beta_7 lncomments +\beta_8 recommended_d+\beta_9 bodylength+\beta_{10} catid_i]\,)\,]\,)$$

This model is used to analyze the effects of a campaign's incentives, thresholds, quality, feedback and transparency on the probability of success. The variables which were chosen to test for these effects are described in the variables section after the model. Additionally, since the graphical description showed differences in success rates between specific categories, a factor variable was included to control for these differences. The distributions of the variables *goal* and *comments* were highly skewed. Therefore, these variables were log-transformed to reduce the sensitivity of the estimates to outliers (Wooldridge, 2015, p. 193).

Dependent variable H.1:

- *stateid*: A binary variable which describes the success of a project. It is set to 1 if the total amount pledged by all backers reaches at least 100 percent of the predetermined project goal within the duration of the campaign.

-Variables of interest to test H.1 (incentives):

- *rewardcount*: The total number of different reward levels for a single project. A larger number of rewards can attract more contributors by providing incentives for a larger number of different preferences. As a result, a larger number of different reward levels is expected to have a positive effect on success probabilities (An et al., 2014, p. 4; Kunz et al., 2016, p. 475).

- *medianrewardprice*: This variable describes the price of the median reward level. According to previous results from behavioral economics research, the middle option bias affects the decisions of backers regarding the selection of their preferred reward levels. Consequently, a higher price for median level rewards is expected to have a positive effect on project success (Simons et al., p. 6).

- Variables used to test for effects of "All-or-nothing"-thresholds:

- *loggoal*: The log transformed value of the goal variable (log base 10). The goal variable describes the threshold value set by the founder which needs to be achieved in order for the project to be successful. According to the current state of research (Mollick, 2014, p. 8; Kuppuswamy and Bayus, 2015, p. 14), a higher goal is expected to reduce the success probability of a project.

- *duration*: A variable which describes the total duration of the project in days. Kickstarter recommends constricting the funding period to 30 days in order to increase success probabilities. Shorter project durations are expected to improve success probabilities of campaigns (Mollick, 2014, p. 8; Cumming et al., 2014, p. 22; Kuppuswamy and Bayus, 2015, p. 14).

- Variables used to test for effects of quality:

- *introvid*: This binary variable is set to 1 if the specific project provides an introductory video. On Kickstarter, campaign starters are strongly encouraged to present their projects in a video to appeal to potential backers. A great number of Kickstarter projects competes for the attention of founders, and comparison of projects can become a time-consuming procedure. Considering this fact, projects with introductory videos can save backers the hassle of reading through the whole project description just to get a first impression and provide information in an entertaining way. Therefore, projects which include this feature are expected to be more successful (Mollick, 2014, p. 8; Cumming et al., 2014, p. 13; Kuppuswamy and Bayus, 2015, p. 14).

- *quickupdate*: A dummy variable which was first introduced by Mollick (2014, p. 8) to control for the presence of an update within three days of the campaign start. Early updates can be interpreted as signs of quality since they express the founder's commitment to a campaign.

- Variables used to test for effects of feedback:

- *lncomments*: The log-transformed value of the total number of entries in the comments section of a campaign. To account for campaigns which received zero comments, a small value (0,5) was added to the comments value. Backers comment on a project if they want to participate in its development and provide feedback. Since comments are the only possibility for backers to voice their opinion on a Kickstarter campaign site, they can be used to determine the level of non-monetary participation by backers. Although founders can also leave comments, they rather react to backers than actively starting a discussion. For this reason, the number of comments can be used as a proxy for feedback from backers. A larger number of comments is expected to have a positive effect on success probabilities of campaigns (Kunz et al., 2016, p. 474).

- *recommended*: A binary variable to control for recommendations by staff members from Kickstarter. A recommendation such as the old "staff-pick"-badge or the new "projects we love"-badge increases awareness of promising campaigns. According to previous research, recommendations are expected to have a positive effect on success probabilities (Kuppuswamy and Bayus, 2015, p. 14; Mollick, 2014, p. 8).

Variable used to test for transparency:

- *bodylength*: This variable describes the length of the textual description on a campaign page in words. A longer campaign description provides more information to potential backers and improves transparency. Therefore an increased number of words in a campaign description is expected to have a positive effect on success odds (Crosetto and Regner, 2014, p. 10; Kunz et al., 2016, p. 470).

Explanatory factor variable:

- *catid*: This numerical value identifies each of the 15 categories in alphabetical order. The categories are: 1 art, 2 comics, 3 crafts, 4 dance, 5 design, 6 fashion, 7 film & video, 8 food, 9 games, 10 journalism, 11 music, 12 photography, 13 publishing, 14 technology, 15 theater. The *catid* variable is used as a factor variable to control for differences in success probabilities between categories.

Model Diagnostics:

The logit model was evaluated regarding potential problems with collinearity and multicollinearity. The correlation matrix which is included of the appendix of this thesis did not reveal any signs of collinearity. Additionally, the variance inflation factor (VIF) was checked to account for the possibility of multicollinearity. Since the VIF for all predictors remained below 2.9, there was no evidence of multicollinearity present (Wooldridge, 2015, p. 98).

In order to test the model specification, additional diagnostic tests were conducted. The Hosmer and Lemeshow goodness of fit test compares the predicted frequency of an outcome to the observed frequency of the same outcome. According to Tabachnick et al. (2001, p. 459), the chi-square statistic of the test is insignificant if the model is specified correctly. Besides the Hosmer and Lemeshow goodness of fit test, Stata's *linktest* command was used to assess possible specification errors. However, the result of the linktest did not reveal any signs of misspecification.

While most of the predictors expected to affect success probabilities of crowdfunding campaigns according to previous research were included in the final model, some of them were excluded. The reasons for eliminating these predictors from the final model are explained in the following part of the thesis.

Variables excluded from the model:

To reduce the complexity of the model, increase the goodness of fit, and focus on campaign elements which improve the coordination between market participants, the following variables were not included in the model:

- *location*: This variable was used in previous research (Mollick, 2014, p. 10) to test whether the location of the founder either attracts backers from the same location or increases success probability. However, the effect of location on pledging behavior does not qualify as an improvement of coordination between market participants but is rather an expression of preference. For this reason, it was not included in this study.

- *images*: A variable to describe the number of images on the campaign page. While the number of images has a positive effect on success probabilities of crowdfunding campaigns according to previous research (Crosetto and Regner, 2014, p. 10), including this variable in the model neither improved the goodness of fit of the model significantly nor was the effect on the odds of success statistically significant.

- *videos*: Apart from the inclusion of an introduction video which is measured by the *introvid* variable, founders can provide additional videos on their campaign page. Similar to the effect of images, additional videos have been known to increase the success probabilities of campaigns. However, regarding the sample used, the inclusion of this variable in the model did not improve the goodness of fit. Furthermore, the effect of the number of videos on the odds of success was insignificant.

- *projectsbacked*: The number of projects actively backed by a founder. This predictor is a modification of a predictor which was used in previous research to test for the effect of a founder's experience on funding (Zvilichovsky et al., 2015, p. 10) and overfunding (Koch, 2016, p. 3). Including this predictor in the model did not improve the goodness of fit of the model. Consequently, it was excluded.

- *projectcount*: This predictor measures the number of projects created by a founder. An increased number of projects indicates a higher level of experience of the founder (Zvilichovsky et al., 2015, p. 10). While the effect of this variable was significant, including it in the model did not improve the goodness of fit of the model.

A comparison of the goodness of fit for the final model and for models which use the excluded variables *images*, *videos, projectsbacked* and *projectcount*: is included in the appendix.

7.2 Results and Discussion for Model H.1

The following results (table 7) for the logit model to test the effects of incentives on campaign success are reported as odds-ratios. Odds are the ratio of the probability of the occurrence of an outcome to the probability of the outcome not occurring, which means that an odds-ratio is the ratio of the probability ratio of an outcome under a treatment effect to the probability ratio of the control group. In the following example, the outcome is success and the treatment effect is the inclusion of an introduction video.

The odds-ratio of success for an introduction video ($[p_i/(1-p_i)]/[p_{ni}/(1-p_{ni})]$) is the ratio of the odds of success if an introduction video is included ($p_i/(1-p_i)$) to the odds of success without the inclusion of an introduction video ($p_{ni}/(1-p_{ni})$). Consequently, an odds-ratio above 1 indicates a positive effect of using an introduction video on the probability of success, while a value below 1 indicates a negative effect.

H.1.: Determinants of Campaign Success (Goal >= 4000 USD)

Campaign Elements	Variables	Odds Ratio	% Change in Odds of Success	Change in Predictor
	DV: stateid			
Incentives:				
H.1.1	rewardcount	1,06156*** (0,003)	6,16%	+ 1 Reward
H.1.2	medianrewardprice	1,00041*** (0,000)	0,04%	+ 1 USD
"aon" – Thresholds:				
	loggoal	0,04125*** (0,002)	-95,88%	900,00%
	duration	0,98430*** (0,001)	-1,57%	+ 1 Day
Quality:				
	introvid	2,64779*** (0,123)	164,78%	Presence of Introduction-Video
	quickupdate	1,25474*** (0,040)	25,47%	Presence of Quickupdate
Feedback:				
	lncomments	3,21783*** (0,040)	221,78%	172,00%
	recommended	2,62929*** (0,104)	162,93%	Recommendation Achievement
Transparency:				
	bodylength	1,00005*** (0,000)	0,01%	+ 1 Word
	N	50315		
	BIC	35373.7		
	CHI^2	34408.8		

*, **, *** indicates significance at the α = 0,5%, α = 0,1% and α = 0,01% level, respectively
SE in parenthesies

Table 7: Effects of predictors on campaign success presented as odds-ratios.

Percentage changes in odds-ratios were added to describe the direction of the treatment effect. In case of continuous independent variables, the odds-ratio describes the change in odds of success if the value of the independent variable increases by one unit. To account for the large sample size which usually leads to statistical significance (Wooldridge, 2015, p. 136), the significance levels for the p-value were scaled down.

In addition to odds-ratios, predicted probabilities and marginal effects will be presented for binary predictors and variables of interest. Predicted probabilities are measured as adjusted predictions at mean values (APM), and marginal effects are measured as the marginal effect of a one unit increase in the continuous variable on the probability of success at mean values (MEM). For variables of interest, both measures are presented graphically. In the logit model, predicted probabilities are obtained by the following formula:

$$Pr(Y=1/X_i)=\frac{e^{\beta_0+\beta_1*X_i+...+\beta_{10}*X_n}}{1+e^{\beta_0+\beta_1*X_i+...+\beta_{10}*X_n}}$$

Where X_1 = *rewardcount*, X_2 = *medianrewardprice*, ... , X_{10} = catid; β_1 ,... , β_{10} are the estimated coefficients of the logit regression and β_0 is the intercept. Marginal effects at means for binary predictors are obtained by increasing the variable of interest by one unit while keeping all other predictors at their mean:

$$Marginal\ Effect\ X_i=Pr(Y=1/X, X_i=1)-Pr(Y=1/X, X_i=0)$$

While the odds-ratio of a specific predictor of interest is applicable at any value of the other predictors, marginal effects depend on the values of the predictor of interest and the values of the other predictors. For instance, considering the odds-ratio of adding an introductory video (2,65), this value holds at any value of the other predictors. Contrary to the odds-ratio, the marginal effect of an introductory video (23,66%) on the probability of success is measured with the other predictors held constant at their means.

For binary variables, table 8 demonstrates the marginal effects of the difference in probabilities at mean values:

Binary Variable (X_i)	Pr ($Y=1 \mid X_i=0$)	Pr ($Y=1 \mid X_i=1$)	Marginal Effect
introvid	33,64%	57,30%	23,66%
recommended	49,81%	71,80%	21,99%
quickupdate	52,20%	57,81%	5,61%

Table 8: Marginal effects of binary predictors at mean values on probability of campaign success.

7.2.1 Variables of Interest (Incentives)

- *rewardcount*: An increase in the number of different reward categories increases the odds of success by 6,16%. This effect confirms findings from previous research (An et al., 2014, p. 4; Kunz et al., 2016, p. 475). Considering the effects of incentive diversification on campaign success, we can conclude that an increased number of distinctive reward categories increases the probability of success significantly. The following graph (figure 9) describes the average of predicted success probabilities for each number of rewards if the number of projects for this reward-count surpasses 10 observations and all other predictors are held constant at their mean values:

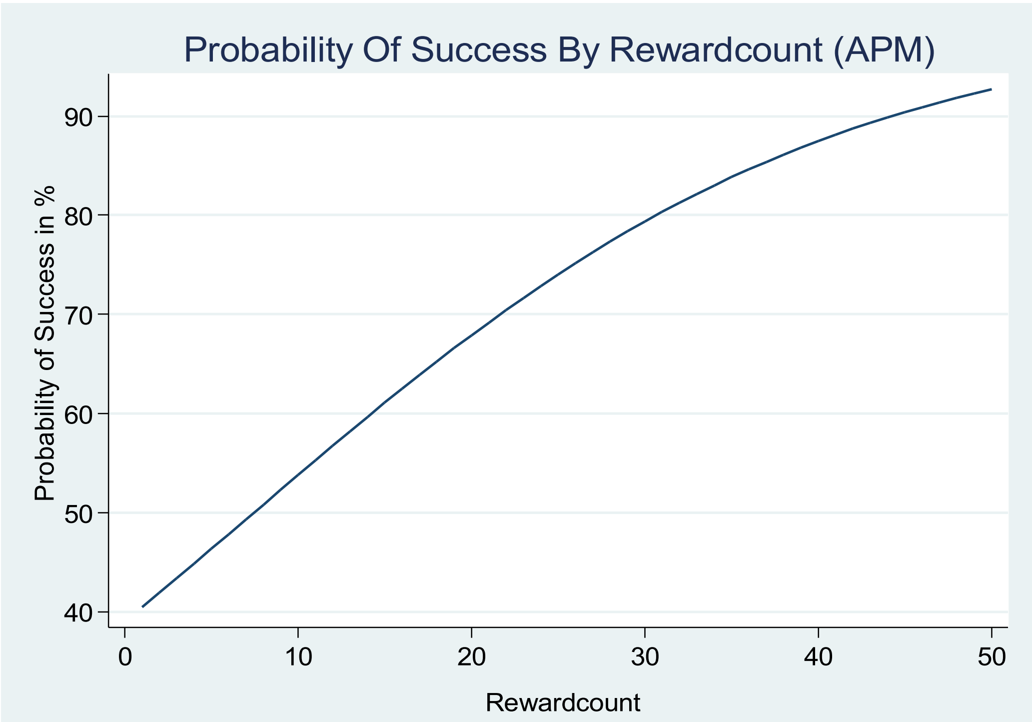

Figure 9: Predicted probability of success at mean values (r*ewardcount*).

The marginal effect at means of each reward level on predicted success probabilities is displayed in figure 10. This graph illustrates that the effect on success probability of adding one additional reward is increasing if the total number of rewards provided is below eight rewards. The marginal effect of additional rewards decreases if a creator provides more than eight different rewards.

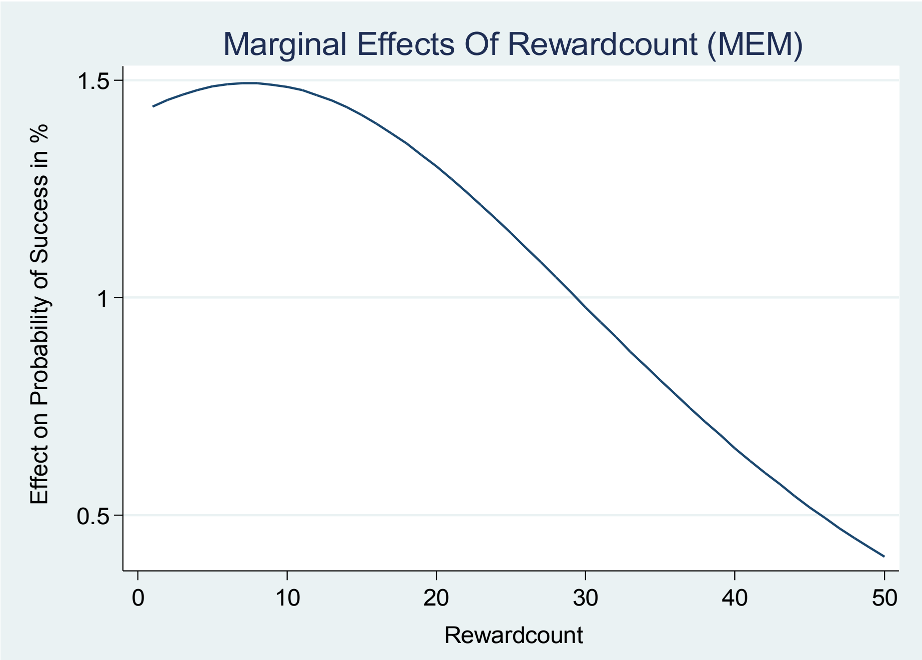

Figure 10: Predicted marginal effect on the probability of success at mean values (*rewardcount*).

- *medianrewardprice*: An increase of the median-reward price by 1 Dollar increases the odds of success by 0,04 %. For example, if the price of a median level reward increases from 100 to 200 dollars, the odds of success increase by 4,18%. A possible cause for this effect is examined in a paper about the middle option bias (Simons et al., p. 6). This result supports the hypothesis that a higher price for the median level reward improves success probabilities for projects.

The following graph, figure 11, describes the average of predicted success probabilities for each price level of median-rewards if this price lies below 2000 USD and all other predictors are held constant at their mean values.

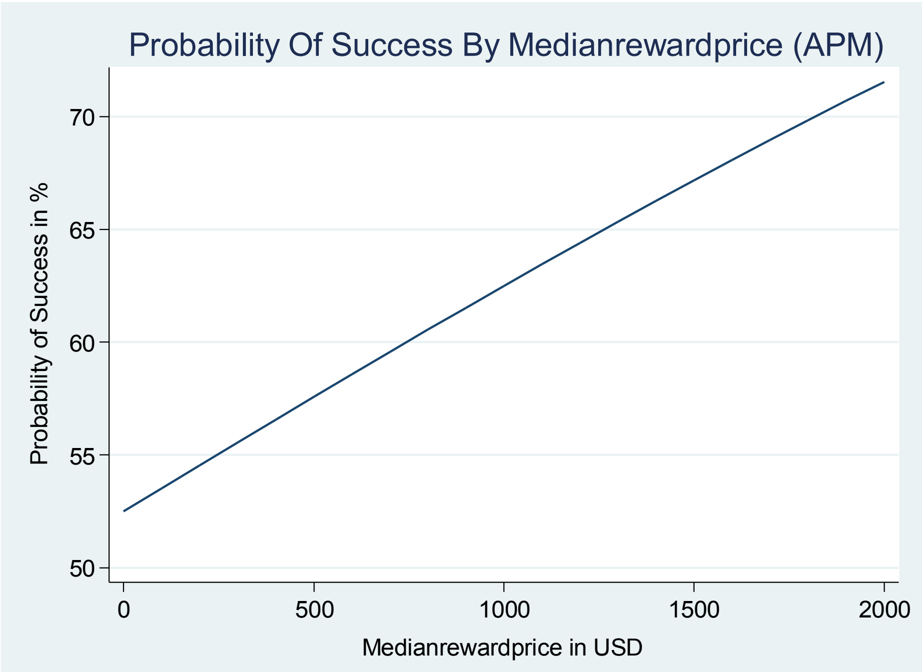

Figure 11: Predicted probability of success at mean values (*medianrewardprice*).

7.2.2 "All-or-nothing"-Threshold Variables

- *loggoal*: An 900% increase of the threshold goal reduces the odds of project success by 96%. This result is in line with previous research (Mollick, 2014, p. 8; Kuppuswamy and Bayus, 2015, p. 14). Higher campaign goals have a negative impact on success probability.

- *duration*: The effect of the duration of a crowdfunding campaign on its success probability has been shown to be negative (Mollick, 2014, p. 8; Cumming et al., 2014, p. 22; Kuppuswamy and Bayus, 2015, p. 14). The project's duration negatively affects success odds (-1,57%) if it is increased by one day.

7.2.3 Quality Variables

- *introvid*: The inclusion of an introductory video increases the odds of success by 164,78% and the MEM by 23,66%. This indicates the great importance of this feature for the presentation of a project to its potential backers. Introduction videos provide several advantages for participants in crowdfunding. Project creators can use their entertainment skills to present their projects to potential backers. At the same time, backers who are browsing casually for an interesting project can get informed about the project while being entertained without spending to much time. The importance of these advantages for success probability has been proven by several research papers (Mollick, 2014, p. 8; Kuppuswamy and Bayus, 2015, p. 14).

- *quickupdate*: Projects increase their odds of success by 25,74% if an update was posted within the first three days of their campaign. This equals a MEM of 5,61%. The effect of a quick-update goes in line with previous research (Mollick, 2014, p. 8).

7.2.4 Feedback Variables

- *lncomments*: A 172% increase in comments for a project increases the odds of success by 222%. Interaction and communication between founders and backers are crucial determinants of crowdfunding success, and the number of comments on a campaign website can be interpreted as a measure of the magnitude of reaction within the supporter base. A project which resonates with backers will be more successful than a project which fails to appeal to backers, therefore a higher number of comments indicates a higher probability of success. This outcome has been observed in previous research (Kunz et al., 2016, p. 474).

- *recommended*: The Kickstarter staff recommendation is highly appreciated by founders because it is known to improve success probabilities for projects which are close to their funding goals (Kuppuswamy and Bayus, 2015, p. 14; Mollick, 2014, p. 8). The odds of success increase by 162,93% if the project gets recommended, while the MEM raises the probability of success by 21,99%.

7.2.5 Transparency Variable

- *bodylength*: The length of the campaign description measured in words has a positive effect on success odds of a campaign. While the change in success odds caused by adding merely one word is quite small, adding 100 words to a campaign description increases the odds of success by 0,5%. This result was to be expected according to previous research (Crosetto and Regner, 2014, p. 10).

7.3 Econometric Model H.2

Overfunding is essentially a special case of success, therefore the model to test H.2 extends the econometric model used to test H.1. However, since the dependent variable which describes the level of overfunding as a percentage of the threshold goal is continuous and not dichotomous, a linear regression model was used instead of a logistic model. This model builds on previous research by Koch (2016, p. 10) who used a linear regression model to measure the effects of campaign elements on overfunding. The predictor *bodylength* which was used to test for the effect of the length of the campaign description on success odds was excluded since it did not improve the goodness of fit of the model. In order to better explain the change in overfunding, additional predictors were included to test for effects of images and community support on overfunding. Furthermore, several predictors (*goal*, *comments*, *medianrewardprice*, *projectsbacked* and *projectcount*) were log-transformed to improve the model's goodness of fit.

H.2: Similar to rewards, stretch goals provide specific incentives for backers to contribute to a campaign even after the funding threshold has been reached. In this way, stretch goals are a measure of utility gained by backers from increased overfunding. Therefore, campaigns which provide stretch goals are expected to achieve higher levels of overfunding than campaigns without stretch goals.

The following formula describes the linear regression model to test H.2:

$$\begin{gathered} lnoverfunded = \beta_0 + \beta_1 stretchgoal_d + \beta_2 rewardcount + \beta_3 lnmedianrewardprice + \beta_4 lngoal + \\ \beta_5 duration + \beta_6 images + \beta_7 introvid_d + \beta_8 quickupdate_d + \beta_9 lncommentsnonzero + \\ \beta_{10} recommended_d + \beta_{11} lnprojectsbacked + \beta_{12} lnprojectcount + \beta_{13} catid_i + \varepsilon \end{gathered}$$

- Dependent variable H.2:

- *lnoverfunded*: The log-transformed value of the *overfunded* variable. The *overfunded* variable describes the amount by which the funding goal of a campaign was exceeded relative to the funding goal. It is determined by calculating the ratio of the funds pledged to the fundinggoal and subtracting 100% ([funds pledged/goal] -1). This method to measure overfunding was applied previously by Koch (2016).

- Variable of interest H.2 (stretch goal):

- *stretchgoal*: A dummy variable to control for stretch goals within a campaign. It takes the value one if an update of a campaign contained the words "S(s)tretchgoal(s)" or "s(S)tretch (-)g(G)oal(s)" and the value zero if stretch goals were not mentioned in any update of the campaign. A similar approach to measure the presence of stretch goals was used in previous research by Li and Jarvenpaa (2015, p. 9). Stretch goals provide a specification of project improvement for predefined levels of overfunding (Koch, 2016, p. 2). While without stretch goals the additional funds from overfunding are not specifically purposed but rather generally used to improve quality, stretch goals provide a measure for backers' additional utility achieved due to overfunding.

- Variables used to test for effects of incentives:

- *rewardcount*: This variable counts the total number of distinctive reward levels for a single project. In previous research, a larger number of different reward levels was found to have a positive effect on success probabilities (An et al., 2014, p. 4; Kunz et al., 2016, p. 475) as well as on overfunding (Koch, 2016, p. 11). However, research by Li and Jarvenpaa (2015, p. 14) which controlled for the presence of stretch goals showed that an increased rewardcount has a negative effect on overfunding.

- *lnmedianrewardprice*: The log-transformed value of the *medianrewardprice* variable, a variable which describes the amount required to access the median-reward. Similar to its effect on the odds of success, a higher price for mid-level rewards is expected to have a positive effect on overfunding (Simons et al., p. 6).

- Variables used to test for effects of "All-or-nothing"-thresholds:

- *lngoal*: The log-transformed value of the goal variable. Previous research (Mollick, 2014, p. 8; Kuppuswamy and Bayus, 2015, p. 14) showed that a higher goal reduces the success probability of a project. Regarding its effect on overfunding, an increased goal is expected to decrease overfunding (Koch, 2016, p. 11).

- *duration*: A shorter project duration is expected to improve success probabilities of campaigns (Mollick, 2014, p. 8; Cumming et al., 2014, p. 22; Kuppuswamy and Bayus, 2015, p. 14) and to increase overfunding (Li and Jarvenpaa, 2015, p. 14). However, previous research by Koch (2016, p. 11) has shown that an increased duration increases overfunding of successful campaigns.

- Variables used to test for effects of quality:

- *images*: A variable used to describe the number of images on the campaign page. An increased number of images is expected to have a positive effect on overfunding since it increases success probabilities of crowdfunding campaigns according to previous research (Crosetto and Regner, 2014, p. 10). Furthermore, previous research has described the positive effect of additional images on overfunding (Koch, 2016, p. 12).

- *quickupdate*: A dummy variable which controls for updates within the first 3 days of a campaign. Similar to its positive effect on success probabilities of campaigns (Mollick, 2014, p. 8), a quickupdate is supposed to increase overfunding.

- *introvid*: According to previous research, the presence of an introductory video has a positive effect on overfunding (Koch, 2016, p. 12). Similar to its positive effect on the probability of success, an introductory video is assumed to increase overfunding.

- Variables used to test for effects of feedback:

- *lncommentsnonzero*: Contrary to the *lncomments* variable which was used in model H.1, no constant was added before log-transformation since campaigns which received zero comments were excluded from the sample. A larger number of comments is expected to increase the level of overfunding (Koch, 2016, p. 12; Li and Jarvenpaa, 2015, p. 14). The positive effect of an increased number of comments on overfunding is to be expected since additional comments have been proven to increase success probabilities of campaigns in previous research (Kunz et al., 2016, p. 474).

- *recommended*: This dummy variable controls for recommendations of campaigns. A recommendation is expected to have a positive effect on overfunding since it increases success probabilities of campaigns (Kuppuswamy and Bayus, 2015, p. 14; Mollick, 2014, p. 8). It works as a catalyst to increase success probabilities since it increases awareness for campaigns close to their funding goal. Recommendations increase not only success probabilities of campaigns, but they also increase overfunding (Koch, 2016, p. 12).

- Variables used to test for effects of community support:

- *lnprojectsbacked*: The log-transformed value of the number of projects supported by a founder through money and feedback. This value is determined by counting the number of campaigns not created by herself which a founder has posted comments on. Since only backers of a campaign can post comments, a comment by a founder other than the campaign's creator indicates this founder's financial contribution. To account for founders who did not comment at all, a small value (0,5) was added to the comments value. Founders who provided financial support and feedback to other campaigns are expected to receive more pledges than founders who failed to do so (Koch, 2016, p. 11; Zvilichovsky et al., 2015, p. 10). Therefore, this variable is assumed to have a positive effect on overfunding.

- *lnprojectcount*: The log-transformed value of the number of projects created by a founder. A larger projectcount is expected to increase levels of overfunding (Koch, 2016, p. 12; Li and Jarvenpaa, 2015, p. 14).

Explanatory factor variable:

- *catid*: Similar to its function in model 1, this numerical value identifies different categories to explain differences in overfunding caused by category-specific funding behavior.

Model Diagnostics:

To test for the violation of Gauss-Markov assumptions, several model specifications were tested. The corresponding test results were included in the appendix. Non-normal distribution of residuals, also called heteroskedasticity, can cause large standard errors which pose a severe problem when testing hypothesis (Wooldridge, 2015, p. 269). While the Breusch Pagan test did not provide any evidence of heteroskedasticity, the standardized normal quantile-plot of residuals showed "heavy tails", a pattern which indicates a large number of extremely positive and negative values. However, when testing for any changes in standard errors with robust regression to account for possible heteroskedasticity, the effect sizes and p-values of the predictors did not change significantly.

As proposed by Wooldridge (2015, p. 306) the general functional form of the model was tested with the Ramsey RESET test. The test result did not indicate any misspecification of the functional form. Similar to the logistic model, the linktest command was used to test for possible misspecification of the model. However, the result was insignificant which means that model misspecification is not evident.

7.4 Results and Discussion for Model H.2

H.2.: Determinants of Overfunding (Goal >= 4000 USD, Comments > 0, Comments <= 708)

Campaign Elements:	Variables	Coefficients	% Change in Overfunding	Change in Predictor
	DV: lnoverfunded			
Incentives:				
H.2	stretchgoal	0,242***	overfunding + 24,2%	Presence of Stretch Goal
		(0,04)		
	rewardcount	0,001	insignificant	+ 1 Reward
		(0,00)		
	lnmedianrewardprice	0,050***	overfunding + 5%	Median Reward Price + 1%
		(0,01)		
"aon" - Thresholds:				
	lngoal	-0,136***	overfunding - 13,6%	Goal + 1%
		(0,01)		
	duration	-0,002**	overfunding - 0,2%	Duration + 1 Day
		(0,00)		
Quality:				
	images	0,003***	overfunding + 0,3%	+ 1 Image
		(0,00)		
	introvid	-0,047	insignificant	Presence of Introduction-Video
		(0,03)		
	quickupdate	0,070***	overfunding + 7%	Presence of Quickupdate
		(0,01)		
Feedback:				
	lncommentsnonzero	0,105***	overfunding + 10,5%	Comments + 1%
		(0,01)		
	recommended	0,072***	overfunding + 7,2%	Recommendation Achievement
		(0,01)		
Community-Support:				
	lnprojectsbacked	-0,004	insignificant	Projects Backed + 1%
		(0,01)		
	lnprojectcount	0,049***	overfunding + 4,9%	Project Count + 1%
		(0,01)		
	N	10389,000		
	BIC	19387,777		
	R2	0,076		

*, **, *** indicates significance at the α = 5%, α = 1% and α = 0,1% level, respectively
SE in parentheses

Table 9: Effects of predictors on overfunding.

Table 9 displays the results of the linear regression model to test the effects of incentives on overfunding. In the following part of the thesis, the results of the linear regression will be discussed.

7.4.1 Variable of Interest H.2 (stretch goal)

-*stretchgoal*: Stretch goals are incentives exclusively available in overfunded campaigns. While rewards are incentives for individual backers, stretch goals are community goals which require collective contributions by backers to reach specified funding thresholds. As expected, the availability of stretch goals significantly increases overfunding by 24,2%. This result goes in line with previous research by Li and Jarvenpaa (2015, p. 14). Furthermore, it proves that backers who contribute beyond the threshold goal are motivated by these specific incentives.

7.4.2 Incentive Variables

-*rewardcount*: Surprisingly, although an increased number of different rewards has a positive effect on a campaign's success probability, its effect on overfunding is insignificant (p-value 0,146). This result contradicts previous research (Koch, 2015, p.11) which did not control for the presence of stretch goals. It also contradicts previous research by Li and Jarvenpaa (2015, p. 14) which did control for stretch goals and found a negative effect of an increased rewardcount on overfunding. Regarding incentives, the presence of stretch goals might be more important for backers who engage in overfunding than a higher diversification of rewards.

-*lnmedianrewardprice*: Judging by its effect on success probabilities, a larger median reward price should also have a positive effect on overfunding. And indeed, increasing the median-reward price by 1% increases overfunding by 0,05%.

7.4.3 "All-or-nothing"- Thresholds Variables

- *lngoal*: The higher a goal is set, the harder it is to reach. This rule is as important in the context of overfunding as it is in the context of achieving funding success. A 1% increase in the specified funding goal decreases overfunding by 0,136%. Considering the effect of a larger goal on success odds, this result was to be expected and goes in line with previous research (Koch, 2015, p.11)

-*duration*: The effect of a longer campaign duration on overfunding is comparable to the negative effect of a longer campaign duration on the probability of success which has been examined in previous research (Mollick, 2014, p. 8; Cumming et al., 2014, p. 22; Kuppuswamy and Bayus, 2015, p. 14). If the campaign duration increases by 1 day, overfunding decreases by 0,17%. While this result contradicts previous research by Koch (2016, p. 11), it concurs with findings from Li and Jarvenpaa (2015, p. 14) who accounted for the presence of stretch goals.

7.4.4 Quality Variables

-*images:* Even though images had no significant effect on the success probability of a campaign, including one more image in a campaign's description increases overfunding by 0,26%. The positive effect of additional images on overfunding concurs with previous research (Koch, 2015, p. 12).

-*introvid:* Contrary to its effect on success probabilities of campaigns, an introduction video has no significant effect on overfunding (p-value 0,129). This result contradicts previous research (Koch, 2015, p. 12) which found a positive effect of providing an introductory video on overfunding. Since the sample used to analyze the effects of campaign elements on overfunding in this thesis was restricted to campaigns with moderate levels of overfunding between 5% and 50%, the effect of an introduction video might be different at extreme values of overfunding.

- *quickupdate:* An update by the founder within 3 days of campaign launch increases overfunding by 7%. This effect is similar to the effect of a quickupdate on success odds and corresponds to the expected influence of a quickupdate on overfunding.

7.4.5 Feedback Variables

-*lncommentsnonzero:* Comments are an important predictor of campaign success, and they furthermore have a significant effect on overfunding. An increase of 1% in the number of comments results in an increase in overfunding of 0,11%. This result was to be expected because of previous research (Koch, 2015, p. 12; Li and Jarvenpaa, 2015, p. 14).

- *recommended:* Similar to its effect on success probabilities, a recommendation by the Kickstarter-Staff increases overfunding by 7,2%. This result concurs with the expected direction of the effect and previous research (Koch, 2015, p. 12).

7.4.6 Community-Support Variables

-*lnprojectsbacked:* There is no significant effect of active support for campaigns by other founders on overfunding (p-value 0,578). Although this result contradicts previous research (Koch, 2016, p. 11; Zvilichovsky et al., 2015, p. 10), we have to consider that the *lnprojectsbacked* variable does not control merely for financial contributions, but for a simultaneous contribution of pledges and feedback.

-*lnprojectcount:* The more experience founders gain by starting campaigns, the more overfunding their campaigns receive. If the number of founded campaigns increases by 1 %, the level of overfunding increases by 0,05%. This result was to be expected considering previous research (Koch, 2015, p. 12; Li and Jarvenpaa, 2015, p. 14).

8 Examples from Kickstarter

In the previous section, the effects of campaign elements on success odds and overfunding were described regarding their size and significance. To demonstrate more comprehensibly how these effects influence success probabilities, this section evaluates Kickstarter campaigns at changed predictor values and compares the outcome to the predicted probability of the campaign's true predictor values.

Additionally, this section predicts the probabilities of success for campaigns at different values of incentive combinations to demonstrate how changes in the number of reward categories and median reward prices can influence success probabilities. The classification table of the logistic regression model which is included in the appendix shows that 84,29% of the observations included in the sample are predicted correctly. The percentage of correctly classified campaigns indicates that this model is suited for the prediction of success probabilities of campaigns. On the other hand, the predictive power of the linear regression model is limited due to the rather low R-squared value of 0.076. Consequently, overfunding will not be analyzed in this section.

8.1 The Mini Mobile Robotic Printer: Prediction of Success

Robotic Printer, Initial Probability Of Success: 85,24695%

Robotic Printer Stats	Predictor	New Value Of Predictor	New Probability Of Success	Change In Pr(Success)
5,602 (400.000)	loggoal -	5 (100.000)	97,52359%	12,28%
5,602 (400.000)	loggoal +	6 (1.000.000)	61,89929%	-23,35%
30	duration -	15	87,99000%	2,74%
30	duration +	45	82,00553%	-3,24%
8	rewardcount -	1	79,18162%	-6,07%
8	rewardcount +	16	90,30900%	5,06%
200	medianrewardprice -	50	84,45537%	-0,79%
200	medianrewardprice +	1000	88,92012%	3,67%
4790	bodylength -	2000	83,28384%	-1,96%
4790	bodylength +	8000	87,26550%	2,02%
1	quickupdate	0	82,15929%	-3,09%
1	introvid	0	68,57612%	-16,67%
6,752 (856)	lncomments -	4,605 (100)	31,97090%	-53,28%
6,752 (856)	lncomments +	7,601 (2000)	93,97060%	8,72%
1	recommended	0	68,72704%	-16,52%

Exponentiated values in parenthesis

Table 10: Robotic Printer, predicted probability of success at designated predictor values.

The columns in table 10 are organized in the following way. The first column, "Robotic Printer Stats", displays the true values of the "Robotic Printer" campaign. The second column, "Predictor", displays the name of the changed predictor for each row and the direction of change. The third column, "New Value Of Predictor", displays the new value of the changed predictor. Column four, "New Probability Of Success", displays the probability of campaign success at the changed predictor value with the other predictors held constant at their true campaign values. The final column displays the difference between the new probability of success for each changed predictor value and the initial probability of success at true campaign values.

The campaign for the mini mobile robotic printer[9] is evaluated as an example of a successful campaign with moderate overfunding. When looking at the original predictor values of the campaign, the values of the binary predictors in particular are very interesting. In the case of the mini mobile robotic printer, the founders provided a quickupdate as well as an introduction video, and their campaign was recommended by the Kickstarter staff. In order to demonstrate how these binary predictors of campaign elements influence the success probability, let us assume that the founders would have provided neither a quickupdate nor an introductory video, and that the campaign would not have received a recommendation by the Kickstarter staff. Under these conditions, each of the binary predictors would equal zero and the probability of success would be reduced by more than half to 39,81 %.

Since the initial probability of campaign success is already quite large, the positive effect of reducing the threshold goal or increasing the number of comments is rather small. However, these two design elements can have a sizable negative effect if the threshold goal is raised or the number of comments is reduced.

The following table (table 11) describes the effect of incentive combinations on success probability. Increasing the reward count to 10 rewards increases success probability by 0,96% even at a lower median-reward price of 100 $. At 30 different reward levels and a median-reward price of 50 $, the success probability would have even surpassed 95%.

Robotic Printer, Evaluation of Success (Pr(Success) = 85,24695%)

Rewardcount	Medianrewardprice	New Probability Of Success	Change in Pr(Success)
8	200	85,24695%	0,00%
10	50	85,96025%	0,71%
10	100	86,20621%	0,96%
10	500	88,04582%	2,80%
20	50	91,75423%	6,51%
20	100	91,90824%	6,66%
20	500	93,04872%	7,80%
30	50	95,28819%	10,04%
30	100	95,37952%	10,13%
30	500	96,05176%	10,80%
40	50	97,35130%	12,10%
40	100	97,40373%	12,16%
40	500	97,78829%	12,54%

Table 11: Robotic Printer, predicted probability of success at different combinations of *rewardcount* and *medianrewardprice*.

9 https://www.kickstarter.com/projects/1686304142/the-mini-mobile-robotic-printer

8.2 XG4 Shoe Insoles (Failed Campaign): Prediction of Success

XG4, Initial Probability Of Success: 18,14%

XG4 Stats	Predictor	New Value Of Predictor	New Probability Of Success	Change In Pr(Success)
4,699 (50.000)	loggoal -	4 (10.000)	67,29895%	49,16%
4,699 (50.000)	loggoal +	5,699 (500.000)	0,90608%	-17,24%
41	duration -	15	25,06364%	6,92%
41	duration +	60	14,09571%	-4,05%
12	rewardcount -	1	10,30446%	-7,84%
12	rewardcount +	24	31,22168%	13,08%
179	medianrewardprice -	20	17,19355%	-0,95%
179	medianrewardprice +	400	19,53002%	1,39%
1114	bodylength -	557	17,70778%	-0,44%
1114	bodylength +	2228	19,03870%	0,90%
0	quickupdate	1	21,75920%	3,62%
1	introvid	0	7,72432%	-10,42%
2,639 (14)	lncomments -	0 (1)	1,00419%	-17,14%
2,639 (14)	lncomments +	3,912 (50)	49,52707%	31,38%
0	recommended	1	36,81952%	18,68%

Exponentiated values in parenthesis

Table 12: XG4, predicted probability of success at designated predictor values.

The Kickstarter campaign for the XG4 shoe insole[10] serves as an example of a failed campaign. Although the founder was ultimately not able to collect 50.000 $, 68 backers were willing to support the project financially and pledged 10.929 $ in total to the campaign. Why exactly did it fail? The prediction of success reveals several problems with the campaign. A quickupdate would have increased success probability by 3,62% and demonstrated the founder's dedication to the quality of the project.

Decreasing the threshold goal to 10.000 $ would have increased success probability by 49,16%, but compared to the average goal of 105.143,5 $ for technology campaigns, 50.000 $ is already a rather modest funding threshold. However, the extended funding period of 41 days should have been restricted to a maximum of 30 days in order to enhance the deadline effect.

In terms of effect size, the number of comments is the second most influential predictor next to the funding goal. The number of comments posted on the XG4's campaign site seems rather low compared to the average of 76,7 comments per campaign in Kickstarter's technology category. Reaching a number of 50 comments would have indicated sufficient interest in the project by Kickstarter's community of backers to raise the XG4's probability of success to 49,53%.

Incentives motivate backers, and even if the average number of rewards in the technology category is below the reward-count of the XG4 campaign, its founder could have provided additional incentives to motivate backers. Regarding the XG4, an increase of 12 rewards would

[10] https://www.kickstarter.com/projects/roarxg4/the-xg4-the-shoe-insole-that-makes-you-faster-real

have raised the probability of success to 31,22% and improved success odds considerably.

The following table demonstrates the effects of different combinations of incentives on the XG4 campaign's estimated success. Providing 20 different reward levels increases success probability by 7,18% even at a rather low price for the median level reward.

XG4, Evaluation of Success (Pr(Success) =18,14312%)

Rewardcount	Medianrewardprice	New Probability Of Success	Change in Pr(Success)
10	50	15,72098%	-2,42%
10	100	15,99493%	-2,15%
10	500	18,32693%	0,18%
12	179	18,14312%	0,00%
20	50	25,31815%	7,18%
20	100	25,70833%	7,57%
20	500	28,96815%	10,83%
30	50	38,12385%	19,98%
30	100	38,60935%	20,47%
30	500	42,56771%	24,42%
40	50	52,82515%	34,68%
40	100	53,33648%	35,19%
40	500	57,39316%	39,25%

Table 13: XG4, predicted probability of success at different combinations of *rewardcount* and *medianrewardprice*.

9 Conclusion

Crowdfunding is a relatively new alternative to traditional investment methods. A growing number not just of entrepreneurs with the intention to start a company, but also of people and communities who want to realize ideas regardless of their profitability, are discovering crowdfunding as a feasible tool to accumulate capital. Increased coverage of successful crowdfunding campaigns in the news raised the popularity of this relatively new investment method.

In order to analyze how crowdfunding can improve coordination between market participants, the efficient use of campaign elements to improve the allocation of funds according to preferences of backers was empirically analyzed in this thesis. Data was obtained from the crowd-berkeley crowdfunding database and the "webrobots.io" webscraping service. The sample consisted exclusively of "All-or Nothing" - campaigns hosted on Kickstarter, one of the largest reward-based crowdfunding platforms in terms of traffic- and market share. Several campaign elements were analyzed regarding their effect on success and overfunding.

Similar to findings from previous research, my results show that projects which are very ambitious in scope are harder to realize since campaigns with larger funding goals and longer durations are less likely to reach or even exceed their goals. Quality elements such as introduction videos and early updates have a positive effect on campaign success and overfunding. These signs of commitment signal the dedication of founders to convince potential backers of their project's quality.

Besides quality- and "aon"-threshold elements, feedback elements are very important since the success of crowdfunding campaigns depends on the active participation of a crowd. Comments and staff recommendations were shown to have a positive influence on success as well as on overfunding which demonstrates the importance of feedback elements for efficient coordination on crowdfunding platforms. Campaign creators who repeatedly launch campaigns become eligible for additional overfunding due to increased community support and experience. However, there is no evidence that backers who actively support other campaigns with money and feedback receive increased overfunding.

Campaign supporters participate in reward-based crowdfunding mainly to gain access to rewards. The more campaign creators adapt to the preferences of backers, the more likely is the successful outcome of a campaign. An increase in the median reward price has a significant positive effect not just on the probability of campaign success, but it furthermore increases overfunding of successful campaigns. While the number of different reward levels has a significant positive effect on campaign success, it has no statistically significant effect on overfunding of campaigns. The presence of stretch goals on the other hand significantly increases overfunding.

There are several limitations of this thesis because of the focus on crowdfunding-specific characteristics. For instance, the role of social networks to increase awareness of a campaign and gain social support was not subject of this thesis. Furthermore, the influence of geographic location on campaign success was not examined since it did not constitute an improvement of coordination. Another limitation concerns the data used which exclusively contained campaigns from the Kickstarter crowdfunding platform. Due to the reward-based "aon" structure of Kickstarter campaigns, the application of findings from this thesis is limited to crowdfunding platforms which offer similar campaign conditions as Kickstarter such as Indiegogo for instance.

In conclusion, it can be said that detailed information about the project, the visual presentation of the campaign, the motivation of backers through incentives and an active community are important requirements of successful crowdfunding campaigns. If creators, contributors and platforms consider the effectiveness of these features, popular projects are more likely to be realized.

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11 Appendix

11.1 Logistic Regression Diagnostics for H.1

Logistic regression		Number of obs =	50,315
		LR chi2(15) =	34408.81
		Prob > chi2 =	0.0000
Log likelihood = -17600.26		Pseudo R2 =	0.4943

stateid	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rewardcount	1.061563	.0030377	20.88	0.000	1.055626	1.067533
medianrewardprice	1.000411	.0000414	9.93	0.000	1.00033	1.000492
loggoal	.0412539	.0020172	-65.20	0.000	.0374839	.0454031
duration	.9842992	.0010977	-14.19	0.000	.9821501	.986453
introvid	2.647793	.1232481	20.92	0.000	2.416923	2.900717
quickupdate	1.254737	.0395312	7.20	0.000	1.179601	1.334659
lncomments	3.217827	.0404465	92.98	0.000	3.139522	3.298086
recommended	2.62929	.1043688	24.35	0.000	2.432486	2.842017
bodylength	1.000053	5.44e-06	9.77	0.000	1.000042	1.000064
catid						
5	2.056604	.1770148	8.38	0.000	1.737347	2.434528
7	2.733307	.133224	20.63	0.000	2.484277	3.007301
9	.1527029	.0112612	-25.48	0.000	.1321523	.1764494
11	2.18452	.1069636	15.96	0.000	1.984621	2.404554
13	.9370115	.0497763	-1.22	0.221	.8443589	1.039831
14	.2626879	.017157	-20.47	0.000	.2311242	.2985621
_cons	38248.94	7311.818	55.20	0.000	26296.65	55633.76

Figure 12: Results of the logistic regression

stateid	Model 1 b/se	Model 2 b/se	Model 3 b/se
loggoal	0.04125***	0.04174***	0.04145***
	(0.00)	(0.00)	(0.00)
duration	0.98430***	0.98415***	0.98430***
	(0.00)	(0.00)	(0.00)
introvid	2.64779***	2.65142***	2.66280***
	(0.12)	(0.12)	(0.12)
quickupdate	1.25474***	1.26193***	1.25685***
	(0.04)	(0.04)	(0.04)
lncomments	3.21783***	3.23094***	3.21742***
	(0.04)	(0.04)	(0.04)
recommended	2.62929***	2.63717***	2.62566***
	(0.10)	(0.10)	(0.10)
medianrewardprice	1.00041***	1.00041***	1.00041***
	(0.00)	(0.00)	(0.00)
rewardcount	1.06156***	1.06290***	1.06149***
	(0.00)	(0.00)	(0.00)
bodylength	1.00005***	1.00006***	1.00005***
	(0.00)	(0.00)	(0.00)
images		0.99678	
		(0.00)	
videos		0.97340*	
		(0.01)	
projectsbacked			0.99558
			(0.00)
projectcount			1.01684*
			(0.01)
category control	Yes	Yes	Yes
N	50315	50315	50315
bic	35373.7	35386.1	35389.1
chi2	34408.8	34418.1	34415.1
p	0	0	0

Exponentiated coefficients

*, **, *** indicates significance at the α = 5%, α = 1% and α = 0,1% level, respectively

Figure 13: Model comparison for H.1 with predictors which were excluded in the final model. Model 1 is the final model, model 2 includes quality elements (*images*, *videos*), model 3 includes elements for community support (*projectsbacked*, *projectcount*)

Logistic model for stateid

Classified	True D	True ~D	Total
+	22486	3895	26381
-	4008	19926	23934
Total	26494	23821	50315

Classified + if predicted Pr(D) >= .5
True D defined as stateid != 0

Sensitivity	Pr(+| D)	84.87%
Specificity	Pr(-|~D)	83.65%
Positive predictive value	Pr(D| +)	85.24%
Negative predictive value	Pr(~D| -)	83.25%
False + rate for true ~D	Pr(+|~D)	16.35%
False - rate for true D	Pr(-| D)	15.13%
False + rate for classified +	Pr(~D| +)	14.76%
False - rate for classified -	Pr(D| -)	16.75%
Correctly classified		84.29%

Figure 14: Classification Table

```
Logistic regression                             Number of obs     =     50,315
                                                LR chi2(2)        =   34409.80
                                                Prob > chi2       =     0.0000
Log likelihood = -17599.763                     Pseudo R2         =     0.4943
```

stateid	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_hat	1.001064	.0089362	112.02	0.000	.9835499	1.018579
_hatsq	-.003762	.0037789	-1.00	0.319	-.0111685	.0036446
_cons	.0085512	.0159173	0.54	0.591	-.0226462	.0397485

Note: 1 failure and 0 successes completely determined.

Figure 15: Linktest for specification errors of the dependent variable

Logistic model for stateid, goodness-of-fit test

```
  (Table collapsed on quantiles of estimated probabilities)

       number of observations =     50315
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =         7.90
                  Prob > chi2 =         0.4437
```

Figure 16: Hosmer-Lemeshow goodness of fit test

(obs=50,315)

	stateid	goal	duration	introvid	quicku~e	comments	recomm~d
stateid	1.0000						
goal	-0.0345	1.0000					
duration	-0.1043	0.0177	1.0000				
introvid	0.2618	-0.0333	-0.0669	1.0000			
quickupdate	0.2610	-0.0044	-0.0939	0.1172	1.0000		
comments	0.0457	0.0115	-0.0161	0.0162	0.0638	1.0000	
recommended	0.3209	-0.0100	-0.0503	0.1602	0.2082	0.0628	1.0000
medianrewa~e	-0.0433	0.0696	0.0351	-0.0457	-0.0255	0.0087	-0.0031
rewardcount	0.3061	-0.0130	-0.0450	0.2473	0.2044	0.0507	0.2204
bodylength	0.1791	0.0003	-0.0569	0.1608	0.2109	0.0646	0.2027

	median~e	rewar~nt	bodyle~h
medianrewa~e	1.0000		
rewardcount	0.0018	1.0000	
bodylength	0.0184	0.3015	1.0000

Figure 17: Correlationmatrix

Collinearity Diagnostics

(obs=50,315)

Variable	VIF	SQRT VIF	Tolerance	R-Squared		Eigenval	Cond Index
stateid	1.95	1.40	0.5121	0.4879	1	7.9579	1.0000
loggoal	1.41	1.19	0.7110	0.2890	2	1.4711	2.3258
duration	1.03	1.02	0.9663	0.0337	3	1.0757	2.7199
introvid	1.14	1.07	0.8793	0.1207	4	1.0303	2.7791
quickupdate	1.26	1.12	0.7913	0.2087	5	1.0199	2.7932
lncomments	2.52	1.59	0.3967	0.6033	6	1.0021	2.8180
recommended	1.24	1.11	0.8077	0.1923	7	0.8000	3.1540
medianrewardprice	1.05	1.03	0.9486	0.0514	8	0.7045	3.3609
rewardcount	1.33	1.15	0.7526	0.2474	9	0.5223	3.9034
bodylength	1.27	1.12	0.7905	0.2095	10	0.4181	4.3627
_Icatid_5	1.71	1.31	0.5854	0.4146	11	0.3550	4.7344
_Icatid_7	2.89	1.70	0.3458	0.6542	12	0.2058	6.2188
_Icatid_9	2.30	1.52	0.4350	0.5650	13	0.1840	6.5762
_Icatid_11	2.68	1.64	0.3736	0.6264	14	0.1143	8.3456
_Icatid_13	2.20	1.48	0.4548	0.5452	15	0.0929	9.2562
_Icatid_14	2.42	1.56	0.4129	0.5871	16	0.0418	13.8040
					17	0.0042	43.2744

Mean VIF 1.77

Condition Number 43.2744

Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)

Det(correlation matrix) 0.0301

Figure 18: Multicollinearity test

```
Logistic regression                             Number of obs     =     50,315
                                                Wald chi2(15)     =   12841.20
                                                Prob > chi2       =     0.0000
Log pseudolikelihood =  -17600.26               Pseudo R2         =     0.4943
```

stateid	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
rewardcount	1.061563	.0034061	18.62	0.000	1.054908	1.06826
medianrewardprice	1.000411	.0000464	8.86	0.000	1.00032	1.000502
loggoal	.0412539	.0019987	-65.80	0.000	.0375167	.0453634
duration	.9842992	.0011325	-13.75	0.000	.982082	.9865214
introvid	2.647793	.1161387	22.20	0.000	2.429676	2.885492
quickupdate	1.254737	.0401138	7.10	0.000	1.178528	1.335874
lncomments	3.217827	.0403667	93.16	0.000	3.139675	3.297925
recommended	2.62929	.1052141	24.16	0.000	2.430954	2.843808
bodylength	1.000053	7.83e-06	6.79	0.000	1.000038	1.000068
catid						
5	2.056604	.170128	8.72	0.000	1.748787	2.418602
7	2.733307	.1354099	20.30	0.000	2.480387	3.012018
9	.1527029	.0116816	-24.57	0.000	.1314412	.177404
11	2.18452	.1080998	15.79	0.000	1.982599	2.407007
13	.9370115	.0507907	-1.20	0.230	.8425692	1.04204
14	.2626879	.0175478	-20.01	0.000	.2304512	.2994339
_cons	38248.94	7214.262	55.94	0.000	26428.43	55356.34

Figure 19: Logit regression, robust standard errors

11.2 Linear Regression Diagnostics for H.2

Summary Statistics of the Sample for H.2.:

Summary Statistics H.2

	Overfunded	Art	Design	Film & Video	Games	Music	Publishing	Technology
goal	17379.8	11873.6	23221.5	21650.1	18330.7	9696.8	11592.2	41678.4
	(26918.2)	(14441.8)	(29249.0)	(32589.6)	(21370.1)	(9323.8)	(12703.8)	(54845.3)
amountpledged	20675.2	13882.5	28429.8	25320.8	22416.6	11421.4	13797.1	50477.3
	(32795.1)	(16634.0)	(37249.2)	(38909.4)	(26580.4)	(11798.5)	(15972.2)	(67434.0)
ratiofunded	1.184	1.171	1.215	1.172	1.222	1.171	1.183	1.214
	(0.116)	(0.112)	(0.127)	(0.110)	(0.124)	(0.109)	(0.115)	(0.125)
comments	28.91	9.330	52.45	16.80	112.9	9.188	10.60	72.20
	(67.98)	(17.78)	(77.19)	(43.10)	(134.4)	(20.12)	(18.00)	(99.86)
updates	13.44	10.15	13.75	14.73	22.25	9.396	13.52	14.24
	(11.32)	(8.999)	(9.481)	(12.66)	(14.11)	(7.779)	(10.30)	(9.435)
duration	34.42	32.98	34.32	34.81	32.73	35.62	33.10	34.43
	(11.22)	(11.68)	(8.706)	(11.95)	(8.997)	(12.40)	(9.757)	(9.565)
rewardcount	12.59	12.55	10.96	13.38	12.27	12.95	11.87	11.27
	(7.180)	(8.277)	(5.808)	(8.405)	(6.019)	(6.626)	(6.757)	(4.903)
medianrewardprice	135.7	130.8	134.9	158.9	81.07	133.5	103.5	199.1
	(152.6)	(118.2)	(230.2)	(139.7)	(95.73)	(127.6)	(96.55)	(295.5)
projectsbacked	1.519	0.763	2.692	0.762	6.815	0.322	1.145	2.151
	(5.055)	(2.494)	(5.478)	(3.006)	(11.65)	(1.022)	(4.170)	(3.468)
projectcount	1.653	1.499	1.638	1.428	3.382	1.375	1.645	1.386
	(2.973)	(1.463)	(2.064)	(1.751)	(6.857)	(2.568)	(2.166)	(1.036)
Observations	10389	718	788	3051	1029	2845	1342	616

mean coefficients; sd in parentheses

Figure 20: Summary Statistics of the Sample for H.2.

Source	SS	df	MS			
Model	319.343715	18	17.7413175	Number of obs	=	10,389
Residual	3865.68721	10,370	.372776009	F(18, 10370)	=	47.59
				Prob > F	=	0.0000
				R-squared	=	0.0763
				Adj R-squared	=	0.0747
Total	4185.03092	10,388	.402871672	Root MSE	=	.61055

lnoverfunded	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
stretchgoal	.2418848	.0387893	6.24	0.000	.1658504	.3179193
rewardcount	.0013476	.0009277	1.45	0.146	-.000471	.0031661
lnmedianrewardp~e	.0502831	.0095065	5.29	0.000	.0316486	.0689176
lngoal	-.1357204	.0105328	-12.89	0.000	-.1563668	-.1150739
duration	-.0016911	.0005438	-3.11	0.002	-.002757	-.0006252
images	.0025712	.0006895	3.73	0.000	.0012196	.0039228
introvid	-.0468033	.0307996	-1.52	0.129	-.1071764	.0135698
quickupdate	.0703367	.0129628	5.43	0.000	.0449272	.0957461
lncommentsnonzero	.1045635	.0060739	17.22	0.000	.0926575	.1164695
recommended	.0722237	.0134189	5.38	0.000	.04592	.0985274
lnprojectsbacked	-.0043273	.0077752	-0.56	0.578	-.0195682	.0109136
lnprojectcount	.0485605	.0129117	3.76	0.000	.023251	.07387
catid						
5	.1221537	.0333693	3.66	0.000	.0567433	.187564
7	.0234005	.0256526	0.91	0.362	-.0268835	.0736845
9	-.002676	.0338103	-0.08	0.937	-.0689506	.0635987
11	.0305686	.0259643	1.18	0.239	-.0203265	.0814637
13	.0530803	.0283758	1.87	0.061	-.0025417	.1087022
14	.1274239	.0357666	3.56	0.000	.0573144	.1975334
_cons	-1.125749	.0899463	-12.52	0.000	-1.302061	-.9494365

Figure 21: Result of the linear regression:

```
Ramsey RESET test using powers of the fitted values of lnoverfunded
       Ho:  model has no omitted variables
               F(3, 10367) =      2.38
                  Prob > F =      0.0680
```

Figure 22: Ramsey RESET test for functional form misspecification:

```
. linktest

      Source |       SS           df       MS      Number of obs   =    10,389
-------------+----------------------------------   F(2, 10386)     =    429.03
       Model |  319.366019         2  159.68301   Prob > F        =    0.0000
    Residual |  3865.66491    10,386  .372199587   R-squared       =    0.0763
-------------+----------------------------------   Adj R-squared   =    0.0761
       Total |  4185.03092    10,388  .402871672   Root MSE        =    .61008

------------------------------------------------------------------------------
lnoverfunded |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   1.125101   .5121917     2.20   0.028     .1211064    2.129095
      _hatsq |    .034003   .1389068     0.24   0.807     -.238281    .3062871
       _cons |   .1139313   .4699158     0.24   0.808    -.8071941    1.035057
------------------------------------------------------------------------------
```

Figure 23: Linktest for specification errors of the dependent variable

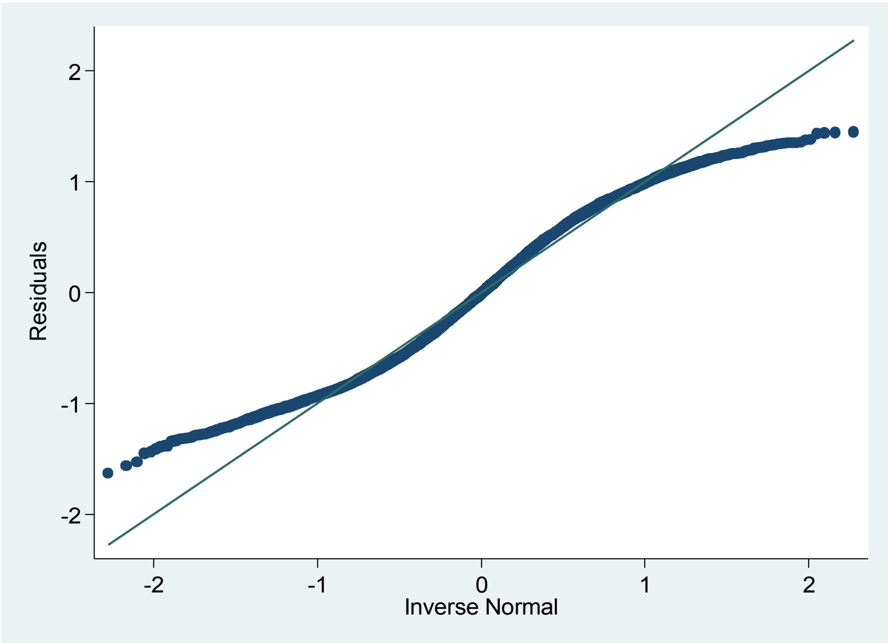

Figure 24: Standardized normal quantile plot of residuals: (qnorm r)

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lnoverfunded

         chi2(1)      =     0.73
         Prob > chi2  =   0.3920
```

Figure 25: Breusch-Pagan test for heteroskedasticity

```
Linear regression                               Number of obs     =     10,389
                                                F(18, 10370)      =      50.58
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0763
                                                Root MSE          =     .61055
```

lnoverfunded	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
stretchgoal	.2418848	.0372283	6.50	0.000	.1689101	.3148595
rewardcount	.0013476	.0009258	1.46	0.146	-.0004673	.0031624
lnmedianrewardp~e	.0502831	.0095818	5.25	0.000	.031501	.0690652
lngoal	-.1357204	.0104948	-12.93	0.000	-.1562922	-.1151485
duration	-.0016911	.0005513	-3.07	0.002	-.0027718	-.0006104
images	.0025712	.0006804	3.78	0.000	.0012374	.003905
introvid	-.0468033	.0311552	-1.50	0.133	-.1078736	.0142669
quickupdate	.0703367	.0130617	5.38	0.000	.0447332	.0959401
lncommentsnonzero	.1045635	.0060427	17.30	0.000	.0927186	.1164084
recommended	.0722237	.0133622	5.41	0.000	.0460312	.0984162
lnprojectsbacked	-.0043273	.0077953	-0.56	0.579	-.0196075	.0109529
lnprojectcount	.0485605	.0130922	3.71	0.000	.0228973	.0742238
catid						
5	.1221537	.0335018	3.65	0.000	.0564838	.1878236
7	.0234005	.0254402	0.92	0.358	-.0264673	.0732683
9	-.002676	.0332926	-0.08	0.936	-.0679359	.0625839
11	.0305686	.0256302	1.19	0.233	-.0196715	.0808088
13	.0530803	.0282249	1.88	0.060	-.0022461	.1084066
14	.1274239	.0358103	3.56	0.000	.0572288	.1976189
_cons	-1.125749	.0897968	-12.54	0.000	-1.301768	-.9497296

Figure 26: Linear regression using robust standard errors

Abstract

Crowdfunding, a method for entrepreneurs to finance projects by calling out to crowds of supporters, is becoming increasingly popular. This master's thesis examines how crowdfunding can improve the coordination between market participants by examining the effect of a campaign's attributes on its outcome. A sample of 50.315 Kickstarter campaigns, one of the largest reward-based crowdfunding platforms, is used to empirically analyze the effects of crowdfunding specific campaign elements on project funding. Primarily, contributors support Kickstarter campaigns financially to gain access to non-monetary compensation also called "rewards". My findings show that increased diversification of distinctive reward-categories increases the amount of funds pledged to a campaign. Regarding the price structure of rewards, a higher price of the median-reward has a positive effect on accumulated funds. Campaigns which try to achieve higher funding goals and last longer are less likely to be successful. Founders who put increased effort into the presentation of their project improve the success probability of their campaign. Another important determinant of campaign success is community support. Campaigns which attract more comments by supporters or even recommendations from the Kickstarter staff receive more funds than campaigns with less community participation.

Abstract (German)

Crowdfunding, eine Methode, mit der Unternehmer ihre Projekte finanzieren indem sie sich an Gruppen von Unterstützern wenden, erfreut sich zunehmender Beliebtheit. Diese Masterarbeit untersucht die Verbesserung der Koordination zwischen Marktteilnehmern durch Crowdfunding, indem sie die Auswirkungen von Kampagnen-Eigenschaften auf das Ergebnis untersucht. Ein Datensatz von 50.315 Kickstarter-Kampagnen, einer der größten Reward-basierten Crowdfunding Plattformen, wurde für eine empirische Analyse der Auswirkungen von Crowdfunding-spezifischen Kampagnen-Features auf die Projektfinanzierung verwendet. In erster Linie finanzieren Unterstützer Projekte auf Kickstarter um Zugang zu nicht monetären Gegenleistungen zu bekommen, die auch als "Rewards" bezeichnet werden. Meine Ergebnisse zeigen, dass eine vermehrte Anzahl unterschiedlicher Reward-Kategorien die Summe der gesammelten Beiträge erhöht. Bezüglich der Preisstruktur hat sich gezeigt, dass sich ein höherer Preis der mittleren Reward-Kategorie positiv auf die Summe der Unterstützungszahlungen auswirkt. Kampagnen mit höheren Finanzierungszielen und längerer Dauer haben geringere Aussichten auf Erfolg. Projektgründer, die mehr Bemühungen in die Präsentation ihres Projektes stecken verbessern die Erfolgswahrscheinlichkeit ihrer Kampagne. Ein weiterer wichtiger Einflussfaktor für den Erfolg einer Kampagne ist die Unterstützung durch die Gemeinschaft. Kampagnen die vermehrt kommentiert werden oder sogar von Kickstarter Mitarbeitern empfohlen werden erhalten mehr finanzielle Mittel als Kampagnen mit geringerer Beteiligung.