Finding your crowd: the determinants of successful reward-based crowdfunding

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**Title:** Finding your crowd: the determinants of successful reward-based crowdfunding

**Summary:**

Reward-based crowdfunding is a rapidly growing way of seeking funding for creative and entrepreneurial projects. Scholarly knowledge on the subject is, for the time being, rather scarce.

I examine the factors which affect the chances of a project successfully receiving the funding it seeks using logit and CLRM models.

I find that several factors play statistically significant parts in explaining the success (or lack thereof) of such projects, including the monetary value of the rewards provided to backers; a result which, to the best of the author’s knowledge, has not been reached before in any published article.

**Key words:** crowdfunding, startup financing, Kickstarter
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1 INTRODUCTION

1.1 An introduction to crowdfunding

In July 2014, the Ohio web developer Zack Danger Brown wanted to make potato salad. Unwilling to pay for the meal himself, he posted an announcement on the website Kickstarter, asking for people all around the world to fund his gastronomical project, stating a funding goal of $10. He promised to reward the people providing the funding by, among other things, saying their name out loud while preparing the carbohydrate-rich side dish and sending them a bite, depending on the size of their contribution. Mr. Brown ended up with total of $55,492 in pledges from potato salad enthusiasts worldwide. (Kickstarter.com)

The concept of financing a venture through a large amount of small contributions from a number of individual backers is by no means a new phenomenon. Not to mention the fact that many charities have functioned using this funding model for decades, Kuppuswamy and Bayus (2014) even mention some of the greatest composers of the Classical era funding their work through the patronage of their listeners.

In spite of this funding model having been around in one form of another for centuries, modern firms have had to wait for the advent of the internet era to begin properly taking advantage of it. In fact, the internet is so central to the way the crowdfunding of today works, that an often quoted definition for it, formulated by Belleflamme, Lambert and Schwienbacher in their article published in 2014 (although the definition was adopted to fairly wide use already from the article's working paper stage), reads as follows: “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.” This definition is built upon the discussion on the spirit of crowdsourcing – the utilization of a crowd to provide pro bono (or sometimes even paid; Bannerman 2013) labor as opposed to financing – by Kleeman, Voß & Rieder in their 2008 article.

Perhaps due to its quite recent surfacing in its current form – wordspy.com, a website that tracks the appearance of new words online, found the first use of the word “crowdfunding” to be from 2006 – research in crowdfunding has so far been scarce to say the least. Very few scientific articles have been written with a clear focus on the
phenomenon. Even fewer have been written from a financial perspective, and only a fraction of those that have been written have been published.

This is understandable, given that crowdfunding challenges many of the conventions of finance, and as such, established financial scholars with established and often highly specific areas of expertise may find the subject to be outside of their comfort zones. Traditional debt financing carries the express promise of a future payment of a certain magnitude at a certain time, and equity financing, while not carrying an express promise of a certain sum at a certain time, is nonetheless driven by the expectation of future payments in the form of dividends and potential increase in value. (Bodie, Kane & Marcus 2009, p. 4) A common factor to both is that the desire to invest is driven (at least in theory) by the expectation of a clear monetary future payoff, the analysis of the size and likelihood of which ideally resulting in a clear numerical answer to the question of which investment to choose. Crowdfunding, on the other hand, is a form of financing with a myriad of possible rewards promised to the backers, ranging from simple mental satisfaction to an elaborate physical compensation “paid” in the form of a special edition of the end product of the backed project, the value of which may in some cases vastly exceed the invested (or, as per crowdfunding lingo, pledged) sum. These rewards are often impossible or, even more often, simply very difficult to put a concrete price tag on.

Even though the story of Mr. Brown is hardly a typical one, even in the world of crowdfunding, it serves to illustrate an important aspect of the funding method: the crowd is capricious and its motivations clearly go beyond the simple assumption of profit-seeking individuals of classical economics. (For such descriptions, see, for example, Smith 1776, p. 246)

1.1.1 Types of crowdfunding

Of course, not all forms of crowdfunding are equally difficult to value in terms of return on investment. Some forms bear more resemblance to traditional financing than philanthropy or pre-ordering. Mollick (2014) divides crowdfunding into four categories based on the nature of expected compensation for the backers. A similar division is made by Bouncken, Kromonek and Kraus (2015). For the purposes of this chapter, the terms used by Mollick are primarily used.
The first category, called **the patronage model**, involves the backers receiving no concrete compensation. This model is essentially philanthropy, and is prevalent in the crowdfunding of artistic and journalistic projects. It is worth mentioning that while no physical compensation is offered, many projects do publish the names of backers who donate a certain sum and/or wish the project to do so. This may arguably carry some value for the backers in the form of positive publicity. However, Mollick (2014) seems to imply that a reward of any kind, even the intangible thanks mentioned here, does constitute reward-based crowdfunding (another type of crowdfunding, described below). This is contrasted by Bouncken, Kromonek and Kraus (2015), who explicitly state that projects offering only immaterial rewards in the form of social acknowledgement adhere to the patronage model (or, in their terminology, the donations model). I find that there is the argument to be made that a simple thank you, even in written and publicized form does not constitute a reward in a sense that could make the instance of crowdfunding significantly different from the patronage model. Then again, de Witt (2012), among others, argues that rewards, even very small ones, are an important part of the Kickstarter experience and a driving motivator to many backers. For the purposes of my study, I will consider any reward, even a publicized thank you, a reward. However, as will be detailed in the method section, these sorts of rewards are not considered to have any monetary value.

The second model, dubbed **the lending model**, bears a close resemblance to traditional debt financing. In this model, backers are promised a certain rate of return on their investment, so the model is actually not significantly different from traditional lending. However, this method of investment may be more accessible to a common individual willing to back a venture than giving out a traditional loan, and as Mollick points out, may carry philanthropic elements in the case of micro-financed loans to projects that, in the view of the backer, promote some form of common good.

The third model, **reward-based crowdfunding**, is the main focus of this study. This model consists of promising backers some concrete non-monetary reward for backing a project. This does not, however, mean the rewards do not have any monetary value – more often than not, they do – but simply that they cannot come in the form of money. The rewards may be very small and largely symbolic – a thank you card with the signatures of the project staff would be an example of this – or very large and elaborate, such as a 7 day boat cruise on the yacht of a friend of the project founder, as offered to backers pledging $8000 or more by the campaign of the alternative media outlet
Russia Insider on Kickstarter.com, the largest reward-based project crowdfunding website at the moment. A special and very common case of reward-based crowdfunding is the pre-order or pre-selling model. In this model, the reward offered to backers is the end product of the project as soon as is finished. Two things about this model are worth noticing. First, the required pledge to receive the end product is relatively often smaller than the intended retail price of the product, so that backers interested in acquiring the product may be driven by calculation rather than altruism. Second, larger pledges are often rewarded with “special editions” of the finished product, with accessories and customization that may otherwise be altogether unavailable.

The fourth and final category presented by Mollick is dubbed as investor crowdfunding. This form of crowdfunding involves giving backers stakes in the ventures they invest in similar to equity or shares of future profits. The most prominent form of crowdfunding in this category, equity crowdfunding, is often subject to heavy regulation, but is rapidly becoming more commonplace. In the effort to encourage equity crowdfunding for small ventures in the United States, the Jumpstart Our Business Startups (JOBS) Act of 2012 includes regulatory exemptions for equity crowdfunding campaigns not exceeding $1,000,000 and meeting certain other criteria.

This is not the only possible way to categorize types of crowdfunding: for example, Belleflamme, Lambert and Schwienbacher (2014) use two categories in their study, dubbed by them as pre-ordering (a subcategory of reward-based crowdfunding) and profit sharing (identical in meaning to investor crowdfunding as described above). This serves to illustrate the fact that few conventions currently exist when it comes to academic research of crowdfunding.

While this dissertation will focus on the third category – specifically, what kinds of factors get backers to contribute in projects financed using that model of crowdfunding –, it is necessary to recognize that the distinction between these categories is not always set in stone. A large number of projects facilitated through Kickstarter, my primary source of data, combine elements of the patronage and reward-based approaches, with small contributions warranting no physical reward and some backers willingly forgoing a reward altogether, while some pledges may be rewarded with products that are explicitly stated to be more valuable than the required pledge.
Since the focus of my study is solely on reward-based crowdfunding, the terms “crowdfunding” and “reward-based crowdfunding”, as well as their derivatives, are used interchangeably for the remainder of the study, unless otherwise specified.

1.2 Purpose of the study

Mollick (2014) constructed a study of the exploratory kind into the dynamics of crowdfunding, studying multiple aspects of crowdfunding without going very deep into any of them. One of the aspects in his study were the factors affecting success rate among crowdfunding campaigns.

It is this aspect of crowdfunding I intend to dig into in my dissertation. My primary contribution will be the addition of new variables – noticeably reward value – into the mix, thereby expanding the existing academic knowledge about this issue. To my knowledge, no published study has to date explored whether the value of the promised reward is a contributing factor to the success rate of crowdfunding campaigns. For this purpose, I have collected data from Kickstarter, the largest website concentrated on reward-based crowdfunding and constructed logistic and classical linear regression models to analyze which variables have a statistically significant impact on the success of a crowdfunding venture and the percentage of its goal a project manages to achieve.

1.3 Limitations

Due to the different rules of different crowdfunding websites, I have concentrated only on projects seeking funding via Kickstarter to make sure the projects have maximal comparability between each other.

I have only included projects in the categories Games and Technology, because I consider these categories to be more likely than others to include projects that offer rewards of monetary value, thus making it easier to assess the effect of said value to the chances of success.

Projects with goals of less than $5000 or equivalent sum are excluded, because projects seeking little funding are likely to follow somewhat different mechanics than the ones with larger goals.
Finally, as background theory is scarce, several limitations concerning the definitions of variables have been set. These are described in more detail in the Method section below.

1.4 The structure of the work

In the next chapter, I will provide a more comprehensive overview of the history and theory of crowdfunding. In chapter 3, some previous studies with relevance to mine are presented. In the fourth chapter, I will present my methodology, including my variables and the models I use. Chapter 5 presents an overview of my data. My results are presented in chapter 6 and discussed in chapter 7. Chapter 8 concludes. Chapter 9 presents a summary of the thesis in Swedish.
2 BACKGROUND AND THEORY

In this chapter, I will present a brief history of crowdfunding, a comparison between crowdfunding and other forms of start-up financing, as well as a synopsis of the theory on the subject.

2.1 Background: the past and present of crowdfunding

2.1.1 Early history

When the Statue of Liberty was first shipped to the U.S. from France, the 46 meter copper lady that was about to become a symbol of the American way worldwide faced a fundamental problem: she had no pedestal to stand on. After the failure or unwillingness of numerous official instances to raise the required funds, the publisher Joseph Pulitzer turned to an unlikely solution. He published a bid in The New York World, a New York newspaper at the time, asking the public for donations to fund the construction and get the statue on her feet. More than 160,000 people chipped in, and the $100,000 needed to complete the pedestal was raised in five months’ time. There was even money left over for a gift to the sculptor. (BBC.com)

This is hardly the first instance of someone asking the public for small donations to fund a large project; as mentioned above, Beethoven and Mozart were about a hundred years ahead of Pulitzer. (And even they can hardly be called pioneers: the Greek philosopher of around 400 BCE, Diogenes, when not sleeping in his barrel or wandering the streets of Corinth with a lamp in his hand during daytime, looking for “an honest person”, was reportedly “funding” his life of what might today be called performance art through donations from kind Corinthians.) (Kuppuswamy & Bayus 2014; Hermitary.com) The example of the statue does not even completely fit the definition of crowdfunding as given above (as there was no internet at the time), but it does serve to illustrate at least two things. First, the idea of harnessing the financial means of a crowd to fund a project it deems worthy has been around for far longer than the 2006-coined term “crowdfunding” has existed. Second, it is essential for a project founder to find a means of communicating their pitch to the masses effectively.
The inception of the internet provided a several magnitudes easier way of doing this. In 1997, the British rock band Marillion raised the $60,000 they needed for their reunion tour in the U.S. through online donations collected from their fans. (Crowdsourcing.org) Fundable.com cites this fundraiser as the earliest known instance of modern-day crowdfunding. However, it wasn’t until the emergence of dedicated crowdfunding platforms that Internet-based crowdfunding really took off. (Freedman & Nutting 2015)

2.1.2 ArtistShare and the internet revolution of crowdfunding

The first truly dedicated crowdfunding (then referred to as fan funding, according to ArtistShare.com) platform of wide renown, launched in 2003 by the programmer and musician Brian Camelio, is called ArtistShare. The site’s primary goal is to enable musicians to seek fan contributions in order to produce digital recordings. The first project, the jazz musician Maria Schneider’s album Concert in a Garden, managed to raise $130,000, enabling all the steps in the production of the album, which went on to win the 2005 Grammy Award for best large jazz ensemble album. (Freedman & Nutting 2015)

This project already bore many of the hallmarks of the modern crowdfunding campaigns we see today. In addition to being funded through an internet-based dedicated platform, it offered a tiered reward system reminiscent of the one seen on Kickstarter today. A contribution of $9.95 allowed the backer to be among the first to download the album upon its 2004 release. Larger contributions were met with rewards of small monetary, but large symbolic value: a $250+ contribution earned the backer a mention in a booklet enclosed with the album as a participant who “helped to make [the] recording possible”. A contribution of $10,000 was promised to be rewarded with a listing as an Executive producer of the album and a dinner with the artist herself. One fan took the offer. (Freedman & Nutting 2015)

Although ArtistShare’s traffic today is modest – estimated by PubDB, a website traffic tracker, to reach a mere 1020 unique visitors daily as opposed to Kickstarter’s nearly 1.5 million – it has managed to produce a steady stream of Grammy award winners, having helped to fund the winners of at least one Grammy winner in 2005-2008, 2011, 2013 and 2014, along with numerous nominees. (ArtistShare.com; PubDB.com) In the wake of its success, the market leaders of today, such as Indiegogo, launched in 2008, Kickstarter, launched in 2009, and the more charity and personal projects oriented
GoFundMe, launched in 2010, were conceived. (Freedman & Nutting 2015; GoFundMe.com)

2.1.3 2009-today: a popularity boom

Since the late 2000s inception of Kickstarter and Indiegogo, the crowdfunding industry has grown at an exponential rate. The amount of funds channeled via crowdfunding has almost or more than doubled each year, growing by 60-80% in 2012, hitting $6.1 billion in 2013, $16.2 billion in 2014 and is expected to soar to $34.4 billion by the end of 2015. (Switter 2013; Crowdsourcing.org) A 2013 report by infoDev, published by the World Bank, estimated the crowdfunding investment market to rise to $93-$96 billion by 2025. If the current rate of expansion continues, this estimate may well prove to have been much too conservative. It is worth noting that the report examines the size of the crowdfunding market as a whole, that is, including all types of crowdfunding.

2.1.4 Kickstarter

The market leader in reward-based crowdfunding, Kickstarter, will be the primary source of data for this dissertation, and I will therefore take a quick look at it in particular.

Kickstarter first went live April 28th 2009. Some of the first projects were not able to reach their funding goals. The first project to actually reach its goal was called drawing for dollars, its sales pitch starting with “I like drawing pictures. and [sic] then i [sic] color them too.” The project raised $35 from three backers, thus exceeding its stated goal of $20. (Kickstarter.com)

From these humble beginnings, Kickstarter very rapidly took off. After just 11 months, in March 2010, the amount of monthly pledges in Kickstarter exceeded a million dollars. Just two months later, the figure was $2 million. And by November of the same year, the figure had permanently climbed to over $4 million. (Businessinsider.com)

Today, Kickstarter reports that altogether almost $2.2 billion have been pledged via its website. The total number of successful projects to date is almost 100,000, and the total number of pledges is almost 28 million by just over 10 million individual backers. The altogether rate of successful financing via Kickstarter is currently 36.40%. (Kickstarter.com)
2.2 Crowdfunding vs. other forms of seed/start-up financing

Even if crowdfunding is hardly traditional at this point, it is rapidly becoming a viable alternative to traditional financing. A 2013 study of Crowdfund Capital Advisors finds that 56% of entrepreneurs who crowdfunded their venture through the use of Pledge/Donation (including reward-based crowdfunding) mechanisms had crowdfunding as their first choice of financing, and the same figure was 52% for those that used Equity or Debt crowdfunding. This indicates that crowdfunding is not a financing choice of last resort, but rather, in most cases, a conscious choice by the entrepreneur.

A direct comparison with other forms of seed financing is problematic, since published studies on the subject do not, to the author’s best knowledge, exist. In this section, I will first briefly go over the other alternatives and then discuss their properties when contrasted to those of reward-based crowdfunding. I will not discuss the potential differences between debt or equity crowdfunding and reward-based crowdfunding, however, for two reasons. First, information on the subject is rather scarce. Second, since these methods actually bear more resemblance to traditional debt and equity financing than to reward-based crowdfunding, for the purposes of this section, they are assumed to follow broadly the same mechanics.

It is also worth noting that while reward-based crowdfunding is often associated with startups, and is indeed often employed by them, not all companies seeking funding to their projects are startups in the sense that the project would be their first or one of their first serious one(s). For example, some relatively established games companies fund some of their projects using Kickstarter. (Kickstarter.com)

2.2.1 Equity

The most common method of seed financing by frequency is owner equity. Out of the 3,972 startups founded in 2004 investigated by Robb and Robertson (2012), 3,093, or more than three out of four, relied in part on the founder’s own means (naturally, any financing choice included in the study did not exclude others). Also Van Auken and Neeley (1996) find it to be the most prevalent form of start-up financing. This is hardly surprising: the owner’s capital does not require any scrutiny and is readily available to the owner at will. In addition, many external financiers may require the owner to
display commitment to their venture through their own equity investment, thus making an owner equity investment a prerequisite for subsequent external financing. This is caused by the informational asymmetries between the entrepreneur and external financiers. (Leland & Pyle 1977) The major downside of this kind of capital is that the risk associated rests solely on the entrepreneur.

Another, though far less prevalent type of equity financing is so called insider equity. In this method, the entrepreneur’s immediate family (parents or spouse) invest in the company’s equity. Robb and Robertson (2012) find this to be rather unusual (only 177 companies out of their sample utilized this sort of financing), but when used, the entrepreneurs, on average, raised slightly more money this way than users of owner equity did using owner equity.

As with insider equity, few firms in Robb and Robertson’s (2012) sample had outsider equity as their source of financing. However, those that did raised substantial amounts of money in this fashion. The average outsider equity investment, when present, was $354,540, far greater than the average owner equity of $40,536. Outsider equity is, in this case, divided into angel investors, venture capital, business equity, government equity and other equity. Of the companies included in Robb and Robertson’s study, only 26 got venture capital financing, but those that did, raised on average $1,162,898 of capital this way. The second and third highest mean investments came from business equity and angel investors, with the mean investments being $321,351 and $244,707, respectively. Investments of other equity were somewhat smaller, with the averages being $187,046 and $146,624, respectively. More than half of the startups that received outside equity financing received it from angel investors: of the 205 firms that received outside equity, 110 were financed by angel investors. The next most prevalent type was business equity, which was received by 56 firms. Government equity and other equity were received by 27 and 8 firms, respectively.

Outside equity may carry benefits that go beyond simple financing. Venture capitalists, for example, often offer help in the strategic planning, and sometimes even in the operative decision-making, of startup companies. (Berger & Udell 1998)

2.2.2 Debt

Like equity, debt is divided into three broad categories by Robb and Robertson (2012).
The first of these is *owner debt*, that is, debt acquired by the entrepreneur’s personal borrowing. This includes the owner's (and possible co-owners’) credit card debt and personal loans.

The next type of debt as specified by Robb and Robertson is *insider debt*. A perhaps slightly surprising observation of theirs is that this type of financing is considerably more common than insider equity financing, as 480 of the 3,972 firms included in the study engaged in this type of financing. Insider debt is also divided into a much greater number of categories: personal and business loans from family are listed separately, as are co-owner’s family and personal loans. Insider loans also include other personal loans, business loans by the owner and business loans by employees. The most common form of insider debt by far is a personal loan to the owner by his family: almost 70% of all insider debt falls into this category.

*Outsider debt* is the second most prevalent method of financing after owner equity, with 1,439 companies in Robb and Robertson’s study utilizing this form of financing. Outsider debt includes business bank loans, personal bank loans, credit line balances, non-bank business loans, personal bank loans by other owners, government business loans and business credit card balances, among others. An interesting observation here is relevance of business credit card financing to startup companies: business credit cards are the second most used type of outsider debt, right after personal bank loans. Like Robb and Robertson (1997), also Van Auken and Neeley (1996) identify outside debt (in their case, from “financial institutions”), as the most prevalent type of startup financing, after the owner’s personal means.

### 2.2.3 Discussion

As mentioned previously, reward-based crowdfunding is a financing method that differs from traditional debt and equity financing on a fundamental enough level to really be considered neither. Unlike debt and equity investors, crowdfunders who fund startups do not expect a payoff in clear monetary terms, but rather in the form of some non-monetary reward, such as the finished product once it is finished, or sometimes even a very nominal reward such as a thank you card from the creators. In addition, many crowdfunders may back projects with small sums expecting no reward of any monetary value whatsoever.
The cost of capital traditionally depends broadly on the investment’s expected rate of return and its risk. (Modigliani & Miller 1958) However, the cost of capital associated with reward-based crowdfunding is a subject that has not seen published studies yet. As Kickstarter does not regulate rewards offered on the site beyond some general guidelines (direct monetary rewards are forbidden, as are rewards in the form of drugs or firearms, to name a few), so entrepreneurs are left to make the decision about reward values on their own. While no published study to date actually states that high rewards lead to a higher number of pledges (this thesis addresses precisely this issue, among others), it is plausible that many entrepreneurs assume this to be the case, as it makes intuitive sense. Thus the apparent trade-off for entrepreneurs becomes one between the certainty and cost of financing. This is not necessarily a point in crowdfunding’s favor (albeit not a point against it in any obvious fashion, either) for the entrepreneur from an objective point of view, but the fact that no monetary return has to be delivered may in and of itself be attractive for the entrepreneur.

As the rewards are generally delivered only once the product has been finished (the product itself often being the reward), one clear reason for an entrepreneur to finance their venture through crowdfunding as opposed to traditional equity or debt may be the fact that they are not required to repay investors at a fixed point. Even though projects do post expected delivery schedules, Mollick (2014) found that only 24.9% of projects delivered on time, but did not report any repercussions to the entrepreneur. Kickstarter does not enforce the delivery of promised rewards – in fact, a disclaimer on the website states that “ Kickstarter does not guarantee projects or investigate a creator's ability to complete their project. It is the responsibility of the project creator to complete their project as promised, and the claims of this project are theirs alone“. (Kickstarter.com) This adds a risk factor to the backing process from the investor’s point of view.

One obvious reason for using reward-based crowdfunding as a method of financing is the ease of access associated with it. Very few rules apply to which projects can seek financing in this way (although Kickstarter does require projects to be “creative”). Unlike traditional methods of financing, setting up a crowdfunding campaign involves no upfront scrutiny of the project’s viability. This does, however, come at the cost of uncertainty. Currently more than 60% of projects listed on Kickstarter fail to meet their financing goal, and thus, as per Kickstarter rules, receive no money whatsoever. This implicitly means that the project must have some sort of mass appeal to be able to finance itself via Kickstarter.
In summary, reward-based crowdfunding is likely to be utilized by entrepreneurs with a novel idea that may not have certain enough prospects to obtain traditional financing (although many of them do not even make an effort to receive it before turning to crowdfunding). It requires less preparation on the part of the entrepreneur than more traditional forms of financing, but the trade-off is that financing in this way is quite uncertain. Then again, there are no apparent sanctions for trying and failing to finance a project in this way. This may lead to entrepreneurs preferring to try this method first, and if it fails, only then turn to more traditional sources. It may also be seen as a more cost-effective method of financing than the traditional forms, although there is little evidence to support this assumption. Finally, it is worth pointing out that just as debt and equity financing do not rule each other out, neither does crowdfunding rule either of them out. In fact, larger and more ambitious crowdfunding projects may well utilize all three forms of financing.

2.3 The actors of crowdfunding

A summarizing literature overview by Bouncken, Komorek and Kraus (2015) describes crowdfunding as a two-sided market, with the subsidy-side, consisting of investors, providing funding to the money-side, consisting of fundraisers, i.e. project creators. In addition to these two sides, there are intermediaries, such as Kickstarter, which facilitate the transmission of funds between these two sides, often in exchange for a fee which may, for example, be a percentage of the total pledged amount. Not all ventures necessarily include an intermediary, as crowdfunding can, in theory, be facilitated through the project creator’s own website, for example. However, this is clearly not a feasible way of communicating the project pitch to the public if the project creator is not very well known to begin with. A venture that does not employ an intermediary is engaging in direct crowdfunding, whereas a project using an intermediary engages in indirect crowdfunding.

2.3.1 Intermediaries

The first group of actors presented by Bouncken, Komorek and Kraus (2015), intermediaries, are the platforms, often internet-based, that facilitate the transmission of funds from investors to fundraisers, functioning as a medium of communicating the project pitch and providing information, as well as executing the process of fund collection.
They follow different rules concerning the treatment of pledges: for example, Kickstarter follows an all-or-nothing model where all pledges are returned to the investor if a specific funding goal is not reached. This is contrasted by the policy of Indiegogo, which allows the project creator to choose between an all-or-nothing model and a model in which the project creator is allowed to keep all of the funds pledged regardless of whether or not the goal is reached. (Kickstarter.com, Indiegogo.com)

In addition to differences in their approach to pledges, many platforms are also dedicated to specific kinds of projects and follow different types of crowdfunding. Indiegogo and Kickstarter are dedicated to “creative” projects (although this definition is rather loose) and they use reward-based crowdfunding, while platforms such as Crowdfunder concentrate on organizational and corporate projects and describes itself as the leader in equity crowdfunding. (Kickstarter.com, Indiegogo.com, Crowdfunder.com)

2.3.2 Fundraisers

Project creators, or fundraisers, are a diverse group, which is understandable, given the ease of access to crowdfunding. (Bouncken, Komorek & Kraus 2015) In a typical case, the fundraiser provides information about their project to the intermediary, which is free to publish or decline the project at its discretion. However, as the example of Mr. Brown’s potato salad shows, not much discretion is used when choosing projects for reward-based crowdfunding on larger platforms. However, other types of crowdfunding may require a significantly greater degree of preparation on the part of the project creator in order to be eligible.

Motivations for fundraisers to turn to crowdfunding vary. As mentioned before, a significant number of entrepreneurs who use crowdfunding as their method of collecting seed financing now turn to crowdfunding as their first choice of capital collection. In addition to the rather obvious goal of collecting funds, especially when access to more traditional methods of financing may be restricted, crowdfunding may provide a valuable channel for customer feedback. (Kleeman, Voß & Rieder 2008, Bouncken, Komorek & Kraus 2015)

Previous studies have recognized the importance of the general characteristics of fundraisers as a major contributing factor in the success of a crowdfunding campaign.
Charitable and non-profit ventures are more likely to meet their funding goals as non-charitable ones. (Bouncken, Komorek & Kraus 2015) This is echoed by Gierczak et al. (2016), who describe certain innovative and creative crowdfunding projects with considerable mass appeal (the reason for such appeal is often hard to pinpoint) as having hedonistic value: simply put, backers feel good about backing these kinds of ventures.

2.3.3 Investors

Investors (known as backers in Kickstarter) are the group of individuals providing the funds for projects in crowdfunding ventures. They screen and ultimately decide which projects to support, bearing a risk and expecting some sort of payoff in the process. (Ordanini et al. 2011, paraphrased in similar fashion by Bouncken, Kramonek and Kraus 2015) They usually are, at least initially, anonymous with respect to each other and the project creator. There are no strict criteria for participating in crowdfunding: naturally, the funds required for a contribution are needed, as is a means of transferring them, but beyond that, few restrictions apply.

The motivations for individuals to participate in the crowd are subject to continuous research, an issue this study is also addressing. Previous evidence shows that factors such as the quality (measured by a number of characteristics) of the project do play a role, however. (Mollick 2014; presented in more detail in the following chapter.)
3 PREVIOUS RESEARCH

As crowdfunding is still in its academic infancy, there is not much theoretical background on which to base one’s analysis of the subject. In this section, I will provide a summary of the knowledge on the subject currently available from the financial perspective. I will not attempt to review all available literature on crowdfunding, since much of it is concerned with aspects that have little relevance for my dissertation, but rather concentrate on the parts that are written from a financial perspective and that concern reward-based crowdfunding in particular. As such, the articles presented in this section are not presented in their entirety. I rather present only the parts that have immediate relevance to my dissertation.

3.1 Belleflamme, Lambert & Schwienbacher 2014 – a theoretical framework

Perhaps the most extensive attempt to form a theoretical framework on the subject of reward-based crowdfunding was constructed by Belleflamme, Lambert and Schwienbacher (2014). While they do not provide an empirical study, they do construct a model for the optimal pricing of the product being funded through the use of game theory. They do this both for pre-ordered products and those that are funded through profit-sharing. As pre-ordering is an important subtype of reward-based crowdfunding, and formal theoretical frameworks on the subject are otherwise non-existent, I will explain their framework concerning this type of crowdfunding in this section. I will not, however, go into detail about the parts of their framework that deal with profit-sharing, as that is outside the scope of this dissertation.

It is also worth noting that since the framework is compressed into a very compact mathematical format that is at times extremely laborious to read, I will, in Appendix 3, open the framework into a somewhat more easily understandable form. I view this as important, since this is, to the best of the author’s knowledge, the only published theoretical framework in the field of reward-based crowdfunding, and thus may provide valuable insights. This does not, however, mean the omission of mathematical details; in fact, I have added several steps that the authors omit from their paper to make the logic of the framework more approachable. In this section, I will limit the
presentation to their assumptions and key findings in the interest of keeping the section reader-friendly. Later in the dissertation, I will use my data and results to assess the degree of applicability of the framework in real life.

### 3.1.1 Assumptions

Belleflamme, Lambert and Schwienbacher view the process of crowdfunding as a two-stage game, the first stage being the crowdfunding stage where the entrepreneur attempts to raise the necessary capital through pre-orders and, if the first stage is successful, the second stage being the product ending up on the market for “regular” (i.e. non-pre-ordering) consumers.

In the study, the authors start by placing two restrictions on their model: first, they assume the entrepreneur to have a monopoly on the product being funded (which, they argue, makes sense, since “crowdfunding initiatives mainly appear on niche markets”) and second, consumers are aware of the product’s characteristics.

The market is assumed to consist of consumers with individual taste parameters, denoted $\theta$. Though formally defined as the “marginal utility for increasing the quality of the good” – since the surplus a consumer derives from consuming the product is defined as $U = \theta s - p$, where $U$ is the surplus derived, $s$ is the baseline quality of the product and $p$ the price of the product – $\theta$ essentially becomes the parameter of the utility a consumer derives from consuming the product in later calculations. This is because the parameter $s$ is normalized to 1 and assumed to remain constant.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K$</td>
<td>Fixed amount of money needed to start production</td>
</tr>
<tr>
<td>$s$</td>
<td>Baseline quality of the good (normalized to 1)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Marginal utility from increasing the quality of the good; it is assumed that this variable is distributed uniformly between $[0,1]$ for consumers</td>
</tr>
<tr>
<td>$n_c$</td>
<td>Number (mass) of crowdfunders</td>
</tr>
<tr>
<td>$\Pi, \pi_1, \pi_2$</td>
<td>Total profits of the entrepreneur ($\Pi$), profits of the entrepreneur in the first period ($\pi_1$) and second period ($\pi_2$), by definition $\Pi = \pi_1 + \pi_2$</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Community benefits for crowdfunders</td>
</tr>
<tr>
<td>$p_c, p_r$</td>
<td>Price charged from crowdfunders ($p_c$) and regular customers ($p_r$)</td>
</tr>
</tbody>
</table>
They also assume that participating in crowdfunding yields some form of extra utility for the funders. This “community benefit” is assumed to come in the form of e.g. having a say in the exact characteristics of the finished product, simple mental satisfaction derived from enabling the existence of a product the consumer views as important, or something of the like. Community benefits are assumed to come at no additional monetary cost to the entrepreneur. Denoted $\sigma$, some consumers are assumed to be willing to pay for this extra utility. For crowdfunders in the presence of community benefits, the total “quality” (its inherent ability to produce utility independent of individual taste) of the product can be expressed as $s + \sigma$. A crowdfunder’s total individual utility thus becomes $\theta(s + \sigma)$, and the additional utility a crowdfunder enjoys over a regular customer becomes $\theta \sigma$. (One can observe from this that the same taste parameter is assumed to apply for both the product and community benefits.)

Consumers who wish to buy the product can choose to pre-order it or buy it on the market for the regular price after its release. However, if the product is to be released at all, it must attract enough pre-orders to satisfy the capital requirement $K$, which is the minimal amount of capital needed to be able to launch the product in the first place. Therefore, for the game to ever move to the second stage, the capital collected in the first stage must satisfy the requirement $K \leq ncp_c$, where $n_c$ is the fraction of consumers of total potential consumers willing to pre-order the product (so $n_c = 1$ would mean that all potential consumers pre-order and $n_c = 0$ would mean that none of them do so) and $p_c$ is the pre-ordering price of the product. If this condition is not satisfied, the crowd receives their money back and the product is never realized.

Having established these conditions, Bellflamme, Lambert and Schwienbacher solve the game backwards to its subgame-perfect Nash equilibrium to find the optimal price for crowdfunders. The exact process from this point on is explained in Appendix 3; the next sub-chapters explains their most important findings.

### 3.1.2 Key findings

The most important findings by Belleflamme, Lambert and Schwienbacher with respect to reward-based crowdfunding of the pre-ordering type can be summarized as follows: the profit accrued by the entrepreneur from a crowdfunding venture of the pre-ordering type is defined by the following rules:
\[ \Pi_p = \begin{cases} \frac{1}{4} + \frac{\sigma^2}{1 + 4\sigma} - K, & K \leq \bar{K} \\ \frac{1}{16} \left( 1 + \frac{8}{1 + 2\sigma} (\bar{R} - K) \right)^2, & \bar{K} \leq K \leq \bar{\bar{K}} \\ 0, & \bar{R} < K \end{cases} \]

\[ \bar{K} = \frac{\sigma(1 + 2\sigma)^2}{(1 + 4\sigma)^2}, \quad \bar{\bar{K}} = \frac{1 + 2\sigma}{8} \]

$\bar{K}$ is the capital accrued before the launch of the product for the general public (that is, during period 1 of the game described by the authors) in optimal conditions and $\bar{\bar{K}}$ is the maximum amount of starting capital that, according to the authors' models, can be raised using the pre-ordering model of crowdfunding. The footer $p$ in $\Pi_p$ simply stands for “pre-ordering”. It is noteworthy that optimal conditions are not always present. As is apparent from the equations, the profits ultimately only depend on the capital required to start production, $K$, and community benefits, $\sigma$.

Another interesting finding by the authors is that in the presence of price discrimination, that is, if the entrepreneur can set a different price to crowdfunders than to regular customers, and if there are nonzero community benefits, crowdfunders will always pay more for the product than other customers.

I will later discuss these findings in the light of the data collected for this dissertation.

### 3.2 Mollick 2014 – an exploratory study

As Ethan Mollick puts it in the executive summary of his 2014 article *The Dynamics of Crowdfunding: an Exploratory Study*, “even basic academic knowledge of the dynamics of crowdfunding is lacking”. It is this general lack of scholarship that he addresses in his study, which aims to answer some basic questions on the subject: what kinds of factors influence the successful financing of a crowdfunding venture (essentially the same subject as that of my dissertation), and what kind of geographical distribution there is in the types and success rates of crowdfunding projects. Unlike
Belleflamme, Lambert and Schwienbacher (2014), he does not propose a theoretical framework on the subject; instead, he conducts an empirical study to shine some light on these essential questions on the subject.

It is worth noting that in this summary of the article, I will omit the part examining the geography of crowdfunding, as this part falls outside the scope of my dissertation.

### 3.2.1 Data and methods

Mollick has collected his data from Kickstarter, the largest website for reward-based crowdfunding, as I have done in this dissertation. To eliminate what he deems to be “non-serious efforts to raise funds”, he eliminates extreme values of fundraising goals (those with a target of less than $100 or more than $1,000,000, 250 in total; in addition, he excludes those with a goal of less than $5000 from the part of his study that concerns the factors of success). Furthermore, he eliminates 3,931 foreign Kickstarter projects since Kickstarter at the time required funders to be US residents, and although these projects were started by US citizens, he deems them to likely be anomalous in some way. This leaves him with a data set of 48,526 projects, representing $237M in pledges. Of these projects, 23,719, or 48.1%, were able to successfully meet their fundraising goals. The official statistics published by Kickstarter at the time put the success rate at a somewhat lower percentage of 44.7%, which Mollick assumes to be in part due to data extraction problems from Kickstarter.

The study considers a number of variables, which are as follows:

- **Project goal**: The amount of funding the entrepreneur seeks.

- **Funding level**: The percentage of the goal that the project manages to raise. If this figure is at least 100, the project is successful in raising the desired amount.

- **Backers**: The amount of funders backing the project.

- **Pledge/Backer**: The mean amount of money pledged by each backer of the project, that is, the amount of money raised divided by the number of backers.

- **Facebook friends of founders (FBF)**: The amount of friends the project’s founders have on the social network site Facebook. This functions as a proxy for the founders’ social networks.
**Category:** The category of the project as categorized by Kickstarter.

**Updates:** The number and timing of updates about the project on the project’s Kickstarter page. This variable is a proxy for the founders’ efforts to reach out to current and potential backers.

**Comments:** The number and timing, among other factors, of comments on the project. Where these comments are collected from remains unclear from the study (the comments sections on projects’ Kickstarter pages seem like a likely alternative). Nonetheless, they are viewed as representative of the emotional resonance of the project, as comments often express enthusiasm or displeasure.

**Duration:** The number of days allowed for the fundraising. An initial maximum of 90 days has been reduced to 60 by Kickstarter, with encouragement to stick to a 30 day time frame.

In addition to these variables, some further variables are introduced in the results section in the study. The ones included in the section of the study that examines the factors leading to successful financing through crowdfunding are as follows:

**Featured:** Whether or not the project is featured, that is, displayed more prominently than most projects on the Kickstarter home page.

**Video:** Whether or not the project’s Kickstarter page features a video presenting the project. Since Kickstarter strongly advises project founders to include a video on their page, including a video is a proxy for a minimum level of preparedness.

**Spelling error:** Whether or not there are spelling errors on the project’s Kickstarter page. Spelling errors are identified with the help of the Oxford English Dictionary’s list of the top 100 most common misspellings, so more uncommon spelling errors and grammatical errors may have been overlooked. This variable is a proxy for quality, since spelling errors indicate a lack of basic proofreading.

Furthermore, the aspect of project updates examines in this case is whether or not the project provides updates within the first three days of launch. He also divides the variable Facebook Friends into four quartiles by the number of friends. Whether each quartile is defined as a quartile of all Facebook users or only those included in the study is unclear, but the latter case seems more likely, since these data is more readily available for the study.
As to the exact method of the study, the paper provides no clear answer. In the part where Mollick examines the factors leading to a crowdfunding venture being successful, it is stated that he uses a logistic regression, but the exact formulation thereof is left unknown, as is the question of which model diagnostics, if any, he runs. That being said, one can get a fairly good picture of his models’ formulations by looking at the table where he presents the results for his regressions. He does also state that “[his] analysis proceeds on the assumption that [their] data is substantially complete”, that is, consisting of virtually the entirety of Kickstarter projects at the time of the writing, which may have lead him to conclude that omitting some of the usual formal statistical analysis may be acceptable.

### 3.2.2 Results

The results of Mollick’s regressions measuring the factors of success in a crowdfunding scheme are summarized in the table below.

*Table 3.2: Summary of results by Mollick*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(goal)</td>
<td>0.23***</td>
<td>0.22***</td>
<td>0.19***</td>
<td>0.23***</td>
<td>0.18***</td>
<td>0.19***</td>
</tr>
<tr>
<td>Duration</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
</tr>
<tr>
<td>Featured</td>
<td>20.47***</td>
<td>22.13***</td>
<td>17.90***</td>
<td>20.45***</td>
<td>19.77***</td>
<td>17.14***</td>
</tr>
<tr>
<td>Video</td>
<td>4.30***</td>
<td>4.27***</td>
<td>4.26***</td>
<td>4.26***</td>
<td>4.26***</td>
<td>4.26***</td>
</tr>
<tr>
<td>Quick update</td>
<td>2.73***</td>
<td>2.69***</td>
<td>2.70***</td>
<td>2.70***</td>
<td>2.70***</td>
<td>2.70***</td>
</tr>
<tr>
<td>Spelling error</td>
<td>0.36***</td>
<td>0.33***</td>
<td>0.38***</td>
<td>0.38***</td>
<td>0.38***</td>
<td>0.38***</td>
</tr>
<tr>
<td>Log(FBF)</td>
<td>2.83***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FBF lower 25 %</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.52***</td>
<td></td>
</tr>
<tr>
<td>FBF 25%-50%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.01</td>
<td></td>
</tr>
<tr>
<td>FBF 50%-75%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.46***</td>
<td></td>
</tr>
<tr>
<td>FBF top 25 %</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.64***</td>
<td></td>
</tr>
<tr>
<td>Category controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>213.59***</td>
<td>19.34***</td>
<td>124.12***</td>
<td>296.63***</td>
<td>9.04***</td>
<td>127.01***</td>
</tr>
<tr>
<td>Observations</td>
<td>22,651</td>
<td>9,603</td>
<td>22,651</td>
<td>22,651</td>
<td>9,603</td>
<td>22,651</td>
</tr>
<tr>
<td>Chi^2</td>
<td>3021.57</td>
<td>1621.44</td>
<td>4578.38</td>
<td>3059.98</td>
<td>2269.24</td>
<td>4935.20</td>
</tr>
<tr>
<td>p</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.10</td>
<td>0.13</td>
<td>0.15</td>
<td>0.10</td>
<td>0.18</td>
<td>0.16</td>
</tr>
</tbody>
</table>

***p<0.01, **p<0.05, *p<0.1

As is evident from the table, nearly all of the examined factors played a statistically significant role in explaining the success of a crowdfunding venture.
The size of the founders’ social networks is clearly an important factor: for example, in the Film category, a founder with 10 Facebook friends had a 9% chance of success in his venture, whereas one with 1000 friends had a chance of 40%. In the table, all of the FBF quartiles besides the lowest one have a positive coefficient (although the second-lowest one isn’t statistically significant; note that Mollick uses odds ratios, so a coefficient of less than one is equivalent to a negative coefficient in a CLRM regression or logistic regression that uses log-odds ratios). The author also notes that having no account linked to the project seems preferable in terms of financing success to having a linked account with few Facebook friends.

The numerous variables that function as proxies for quality and preparedness are also predictors of success in all of the models that include them. Holding everything else equal, the author notes that projects with spelling errors (even though the majority projects with spelling errors only contain one of them) lowers the chances of successful financing by 13%, omitting adding a video by 26% and not updating the page within three days by 13%.

One aspect of the study worth noting is that the pseudo $R^2$ for all of the models is rather low. The highest pseudo $R^2$, 0.18, is found with model 5, that is, the model containing all of the variables except for the different percentiles of FBF. This suggests that the models omit some important variables, and do not thereby fit the data especially well. The constant coefficients are also very high for most of the models, which may also signal omitted explanatory variables. All of this suggests that more variables are needed to capture the full extent of the crowdfunding backer phenomenon.

### 3.3 Colombo, Franzoni & Rossi-Lamastra (2015)

In their 2015 study, Colombo, Franzoni and Rossi-Lamastra set out to fill the gaps in the academic knowledge about the roles of attraction of early contributions and social networks in the success of a reward-based crowdfunding campaign. In addition to an empirical section, they build on previous studies to construct a theoretical framework in an effort to explain the relationships between their factors of interest and the success of a crowdfunding campaign. As a particularly interesting aspect from my point of view,
they also consider the rewards a project offers. However, they do not assess their monetary value, but their general type, making their study complementary to mine.

### 3.3.1 Theoretical formulation

In the authors’ view, participants in a crowdfunding campaign face a high degree of uncertainty about the final delivery date and quality of the product. They argue that a large amount of backing in the early stages of the project helps reduce this uncertainty in three main ways, thus encouraging further backing.

The first mechanism, dubbed *observational learning*, essentially describes flock behavior. As more and more people trust a project and/or its initiators enough to back the project, the suspicions of new potential backers are alleviated, thus lowering the psychological threshold of participating in the funding.

The second mechanism, *word-of-mouth*, functions through existing backers informing their friends and acquaintances about the project’s existence. This effect is enhanced by online social networks, ensuring that individual backers may easily reach a large audience with information about the project. (Author’s note: this mechanism may well be enhanced by the tendency of consumers to expose themselves to information that strengthens their pre-existing beliefs and justifies their consumption decisions. This is done to avoid or alleviate the psychological discomfort caused by cognitive dissonance arising from negative information and/or experiences associated with an already made consumption decision. As such, existing backers of a crowdfunding project are likely to seek out and believe positive information about a project and its creators, and may thus be more likely to also repeat this information to others. See, for example, Sweeney, Hausknecht and Soutar, 2000.)

Third, as most crowdfunding campaigns collect funding for projects that are in early stages of development, backers may contribute their knowledge and wishes to the design process, making it more likely that the final product will suit their needs. Kickstarter, for example, provides a comment section in which backers may present their questions and suggestions to project creators.

These factors are assumed by the authors to make a surge of early backers an important factor in the ultimate success of a project. However, that begs the question of what attracts these early backers, who cannot be influenced by these factors, to a project. To
examine this, the authors construct some hypotheses about the role of social capital in the early stages of a crowdfunding campaign.

They recognize that in addition to traditional relationships consisting of friends, family and acquaintances, dubbed *external social capital*, initiators of crowdfunding campaigns may also form relationships between each other and backers within the crowdfunding platform, calling this type of social capital *internal*. They argue that internal social capital, often, in their view, ignored in previous studies on the subject, is important due to factors such as reciprocity and mutual identification. The former refers to previous help to other project creators creating a sense of obligation to return the favor, and the latter to a sense of community between project creators, which has culminated in organized efforts to use a small percentage of proceeds collected via Kickstarter to help other project creators along with their projects.

With these assumptions in mind, they construct the following hypotheses:

**Hypothesis 1a:** Project proponents' internal social capital has a positive effect on the number of early backers of crowdfunding campaigns.

**Hypothesis 1b:** Project proponents' internal social capital has a positive effect on the amount of early capital raised of crowdfunding campaigns.

Combining the two theoretical frameworks, they further coin the following:

**Hypothesis 2:** The number of early backers and the amount of early capital mediate the positive effect of project proponents' internal social capital on the success of crowdfunding campaigns.

### 3.3.2 Data and method

As Mollick (2014) did, Colombo, Franzoni and Rossi-Lamastra use Kickstarter as their source of data. They concentrate on four categories: technology, video games (as called by the authors – it is unclear if they have actually excluded projects within the games category that aren’t video games or if this is a slight misnomer), film and video, and design.

They divide their explanatory variables in three sets. The first one, related to project characteristics, includes the variables of project category, duration of the campaign, target capital in dollars, number of visuals (images and videos) in the project
description and number of links to external websites with more information on the project, as well as the following characteristics of the rewards offered: customized (meaning the backer can impact the exact contents of the reward), ego-boosting (referring to a publicized thank you) and community-belonging (referring to rewards which include social interaction with either the project creators or other backers). The reward categories are not mutually exclusive, as Kickstarter projects may offer multiple rewards that may fit into different categories.

The second set, related to project proponents, includes variables of internal social capital (represented by the number of other Kickstarter projects that the project creator had backed), number of the project creator’s LinkedIn contacts, whether the proponent was located in the US, and whether the proponent was a company or an individual and in the latter case, their gender.

A third set, related to the campaign and its outcomes, includes variables for the number of backers a campaign has received during the first sixth of its duration and the amount of capital it has managed to amass during this time.

Since it is rather obvious that projects that have amassed all or nearly all of their funding goal during the first sixth of campaign duration have a very high chance (or, in the former case, certainty) of success, the authors leave out the entirety of the top quartile of projects in terms of funding collected during this period. This leaves them with 502 observations.

The authors construct a number of models to test their hypotheses, using probit and tobit models.

### 3.3.3 Results

The authors construct three sets of models to test their hypotheses, most of which include at least partially the same variables. In the interest of summarization, only the results of the third one, which includes the greatest amount of variables and multiple models, is presented here in full. However, the other two models exhibited broadly similar results. The type of regression used in the models presented is probit, and the dependent variable, as in Mollick’s 2014 study and this study, is the binary variable of successful funding.
As one can see from figure 2.3, both of the authors’ first hypotheses clearly hold: both the number of early backers and the amount of early capital are clearly predicting factors in the success of a crowdfunding campaign.

Table 3.3: Summary of results by Colombo, Franzoni and Rossi-Lamastra

<table>
<thead>
<tr>
<th></th>
<th>Model I</th>
<th>Model II</th>
<th>Model III</th>
<th>Model IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal_Social_Capital</td>
<td>0.52**</td>
<td>0.21</td>
<td>0.33</td>
<td>0.26</td>
</tr>
<tr>
<td>Ln_Early_BACKERS</td>
<td>0.662***</td>
<td></td>
<td></td>
<td>0.235***</td>
</tr>
<tr>
<td>Early_Capital</td>
<td>9.596***</td>
<td>7.571***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>External_Linkedin</td>
<td>0.01</td>
<td>-0.05</td>
<td>0.075</td>
<td>-0.079</td>
</tr>
<tr>
<td>D_Individual_Male</td>
<td>-0.618***</td>
<td>-0.400**</td>
<td>-0.482**</td>
<td>-0.430**</td>
</tr>
<tr>
<td>D_Individual_Female</td>
<td>0.074</td>
<td>0.173</td>
<td>0.253</td>
<td>0.244</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.002</td>
<td>0.006</td>
<td>0.004</td>
<td>0.001</td>
</tr>
<tr>
<td>D_Ego_Boosting</td>
<td>-0.414**</td>
<td>-0.392**</td>
<td>-0.406*</td>
<td>-0.394*</td>
</tr>
<tr>
<td>D_Community_Belonging</td>
<td>0.417***</td>
<td>0.558***</td>
<td>0.621***</td>
<td>0.632***</td>
</tr>
<tr>
<td>D_Customized</td>
<td>0.265*</td>
<td>0.179</td>
<td>0.123</td>
<td>0.116</td>
</tr>
<tr>
<td>Ln_Visuals</td>
<td>0.158</td>
<td>0.115</td>
<td>0.073</td>
<td>0.075</td>
</tr>
<tr>
<td>More_Information</td>
<td>0.025</td>
<td>0.01</td>
<td>-0.023</td>
<td>-0.019</td>
</tr>
<tr>
<td>D_USA</td>
<td>0.699***</td>
<td>0.984***</td>
<td>0.625*</td>
<td>0.743***</td>
</tr>
<tr>
<td>Ln_Target_Capital</td>
<td>-0.223***</td>
<td>-0.582***</td>
<td>-0.202***</td>
<td>-0.332***</td>
</tr>
<tr>
<td>Project category dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.480***</td>
<td>-2.519***</td>
<td>-2.309***</td>
<td>-2.519***</td>
</tr>
<tr>
<td>McFadden's Pseudo R²</td>
<td><strong>0.19</strong></td>
<td>0.326</td>
<td>0.378</td>
<td>0.386</td>
</tr>
</tbody>
</table>

***p<0.01, **p<0.05, *p<0.1

They also find that a project creator being male has a significant negative effect on the chances of success, indicating that females and companies have a higher chance of success. Duration, visuals, more information or LinkedIn contacts were not found to have a statistically significant impact on chances of success on any significance level in any of the models, whereas offering customized rewards only had significance on the very modest 10% level and only in one of the models.

The project creator being based in the USA was a significant predictor of success, while the amount of target capital had a significant negative effect on success chances, a result previously reached by Mollick (2014) and replicated in this study.

Interestingly, internal social capital only had statistical significance in the first model, which did not include either the number of early backers or the amount of early capital raised. When these variables (which were statistically highly significant in all models they were included in) were introduced, first one by one and later both at the same
time, this significance vanished immediately. In light of this result, as well as further analysis conducted using the statistics program Stata, the authors conclude that also their second hypothesis holds, and that the amount of early backers and early capital fully mediate the positive impact of internal social capital on a project’s ultimate success.

The pseudo R² values are somewhat higher than Mollick’s (2014) indicating that while the authors concentrate on different factors than Mollick, their models manage to capture a somewhat higher percentage of the factors affecting a project’s chances of success than Mollick’s does. (This must, however, be taken with slight caution considering the unknown exact nature of Mollick’s pseudo R².) However, it is worth noting that their variables include the amount of capital raised up to a certain point, and it would be highly surprising if this did not have a significant impact on success, even if the very highest amounts are excluded.
4 METHOD

As the main purpose of my study is to find out the factors leading to a successful crowdfunding campaign, the dependent variable being either success (1) or failure (0) to raise the sought-after amount of funds, the dependent variable in the primary part of my study is clearly binary. As such, I am left with the alternatives of using a probit or logit model.

According to Brooks (2008, p. 518), the models are functionally nearly identical in most cases, with the exception of cases where distribution between 0 and 1 is very unbalanced. Since the current stats on Kickstarter state that the overall success rate on projects is 38.31%, the balance does not seem uneven enough to make much of a difference between the two alternatives. However, it is worth noting that the Games and Technology categories do have the somewhat lower success rates of 32.89% and 20.18%, respectively. (Kickstarter.com) On the other hand, Brooks (2008) does not specify that either of the possible models would somehow be better in the case of uneven distribution, and even goes on to call the choice between the models “usually arbitrary”.

Of the studies published to date, Mollick’s is the one that by far the most resembles mine, and as such, is my most important benchmark. I have thus opted for the logit model in the interest of maintaining maximal comparability to that study. It is also noteworthy that Brooks (2008, p. 518) mentions that the logistic model is traditionally preferred (although he speculates that this is likely due to computational challenges that no longer apply). Nonetheless, more factors in this case argue for the logit than probit model, and therefore the choice is a rather easy one.

My model, following the standard formulation of a logit model (created by Cox in 1958) presented by Brooks (2008, p. 514), is as follows:

\[ P_i = \frac{1}{1 + e^{-(\beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \beta_7 x_{7i} + \beta_8 x_{8i} + \beta_9 x_{9i} + \beta_{10} x_{10i} + \beta_{11} x_{11i} + \beta_{12} x_{12i} + u_i)}} \]  

(2)

In this model, the coefficients are denoted \( \beta_n \) and \( u_i \) is the error term.
In addition, to look at the phenomenon from a slightly different angle, I will run a classical linear regression model (CLRM) with the same independent variables as in the logit model and with the percentage of funding goal achieved as the dependent variable. I will again run it multiple times omitting some variables to find the best fit and compare significance levels achieved using different models. The largest classical linear regression model in question is the following.

$$y_i = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \beta_7 x_{7i} + \beta_8 x_{8i} + \beta_9 x_{9i} + \beta_{10} x_{10i}$$

(3)

In the next subsection, I will go through the individual independent variables.

### 4.1 The independent variables

In this section, I will go through the independent variables in the above equation. The variables are divided into those used by Mollick (2014) (or equivalent) and those introduced for this dissertation. This division is made for the sake of clarity, since the ones introduced by me naturally require more clarification, as they have not been discussed in the previous studies section. It is worth noting that I have excluded Mollick’s Spelling error variable, since as a non-native English speaker I may not be able to rely on my own assessment, and found no feasible way of including it without unreasonably adding to the time my data collection would have taken. I have also excluded the amount of comments on a project’s page as an explanatory variable. While this may be the best available indicator of the amount of emotion the project is able to stir up, comments are restricted to backers, which means the possible pool of commentators grows in direct proportion to the number of backers a project has – making it likely that any positive correlation between the amount of comments would have a “backwards” causality. However, if this issue could be solved, future studies on the subject would perhaps be able to utilize the amount of comments as an explanatory variable – the amount of comments varies greatly, with the greatest amounts reserved to projects that not only reach, but far exceed their funding target.

As Kickstarter projects may nowadays collect funding in a variety of different currencies, the face amounts of project funding goals, total sums pledged and pledge
thresholds for reward levels for non-USD-denominated projects are converted to USD using the exchange rate of the project’s end date, acquired from Exchangerates.co.uk.

It is worth noting that the variables that had no statistical significance in any of the models were omitted from the final models presented in the results section in the interest of keeping models parsimonious. These variables are, however, presented here, since their effects were also studied, even if the models that contain them are not presented in full.

4.1.1 Mollick’s variables

\( x_{2i} = \ln(\text{Goal}) \): The stated goal of the fundraising campaign. If the goal is not reached, all funds are returned to backers. A logarithm is taken to induce normality.

\( x_{3i} = \ln(\text{Duration}) \): The duration of the campaign. In most cases, 30 days. A logarithm is taken to induce normality.

\( x_{4i} = \text{Staff pick} \): Whether or not the campaign is chosen as a Staff Pick by Kickstarter. While this variable was not, as such, introduced by Mollick, it is chosen to replace the Featured variable used by him, essentially because, unlike being Featured, being Staff Picked is a permanent state that is easier to verify than having been Featured at some point, while being otherwise very similar to the Featured state in terms of its effects and the conditions required to acquire this status. Staff Picks are projects that are picked by the Kickstarter staff as their personal favorites, and they receive special visibility.

\( x_{5i} = \text{Video} \): Whether or not the campaign page has a video.

\( x_{5i} = \text{Quick update} \): Whether or not the founder posts an update within the first three days of fundraising.

\( x_{6i} = \ln(\text{FBF}) \): The amount of Facebook friends of the founder, if a Facebook account is linked to the project. Once again, a logarithm is taken to induce normality. As more than half (157) of the projects have no Facebook account linked to them, some models only include FBF as a dummy variable, indicating whether or not a Facebook account is connected to the project. It is also worth noting that three projects that had Facebook connected to them had creators with no (publicly displayed) Facebook friends. These projects were excluded from the sub-sample that examines this phenomenon in detail, since the profiles in question were likely created for the purpose of registering the
creator to Kickstarter, and, as such, are not true measures of the creator’s social networking or connectedness.

4.1.2 Variables introduced for this dissertation

\( x_{7i} = \text{Publicity} \): Whether or not the campaign is mentioned by an independent media outlet before or during the campaign. This is discovered by conducting two searches using the internet search engine Google: the project’s name, and the founder’s name with a keyword related to the project. The search is limited to the two first pages of search results to eliminate the most obscure outlets.

An independent media outlet is defined as a website (or magazine, newspaper, TV channel or similar, with online presence for the sake of data collection feasibility) not dedicated to the project, with an article either about the outlet itself, or an article about the outlet’s parent company that mentions the outlet by name in the English version of the online encyclopedia Wikipedia, again, to exclude the most obscure outlets. In addition, websites which routinely collect some basic data on all similar projects and offer no reliable indication that any single project of a certain kind would stand out are likewise excluded. This includes websites that track the progress of all or most Kickstarter projects (such as Kicktraq.com), as well as websites dedicated to specific kinds of projects or products (such as Boardgamegeek.com, which is a database of board games). Also, websites that specialize in publishing unedited press statements from project creators (or other sources) are excluded, since it is next to impossible to verify that these would reach the intended audience or be otherwise indicative of the project receiving attention.

\( x_{8i} = \text{Reward value} \): A rough estimate of the value of reward awarded to the backers relative to the pledged amount. As the exact quantification of the reward value is often hard or even impossible, this value is limited to just four categories: none, low, intermediate and high, to minimize the effect of pricing inaccuracies. The “none” category is solely reserved for reward levels with no tangible monetary value. The “low” category is defined as a reward level with monetary value of less than 75% of the pledged amount, the intermediate category as 75% to 125% of the pledged amount (thus likely containing most of the projects that follow the pre-ordering model), and the high category covers projects whose reward level exceeds 125% of the pledged amount. These limits are decided based on the assumption that inaccuracies in the pricing of the product are unlikely to be so vast as to exceed 25% of the pledged amount. However, as
there is no prior theory on which to base this assumption, making the assumption subjective, a sensitivity analysis is conducted to see whether loosening or tightening these assumptions leads to changes in my results.

As most projects offer a tiered reward system, with different values of rewards for different levels of pledges, a simple average of the values of different rewards is calculated with the assigned values of 0 for no reward of tangible value, 1 for low rewards, 2 for intermediate rewards and 3 for high rewards.

To account for the monetary value of the rewards, only rewards with clear, undisputable monetary value are accepted – this effectively limits the accepted rewards to tangible or digital goods and widely-sold services. Thus, rewards such as lavish ways of thanking the backers or guided tours of the firm’s headquarters are considered to have zero value, even if they might require substantial labor contributions from the founders to realize. On the other hand, a reward may include transportation to receive such intangible rewards, which is considered to have monetary value – even if a cursory examination of Kickstarter reveals rewards that include transportation to be seemingly invariably reserved for the highest pledges, far above the transport costs, so these rewards will fall in the “low” category in the overwhelming majority of cases. Digital goods that clearly have a low value that cannot be established with full accuracy, but are nonetheless the backer’s to keep, are considered to have low but nonzero value (i.e. if they comprise the entirety of the reward of a certain level, the reward value is considered to be 1, regardless of the required pledge). Examples of such rewards include virtual currency in a so far unpublished video game and the soundtrack of such a game. Digital goods that are the backer’s to keep, but have no practical applications or value, such as updates on a project by email, are considered to have zero value.

These limitations lead to a situation where many rewards that are considered to be above the “low” category follow the pre-ordering model. In cases where the pre-ordering model is in fact applied, the value of the finished product is defined by the following rules:

- If the intended retail price is stated on the project’s Kickstarter page (or otherwise found easily), this price is used.

- If the intended retail price is not stated, the retail price of a similar product is used.
- If no similar products can be found, or the project advertises itself as a considerably more affordable alternative to existing products while not stating an intended price, the project is excluded.

- “Limited edition” of the product is not considered more valuable than the standard edition, unless it has
  
o a higher stated intended retail price or
  
o some kind of clear functional improvements compared with the standard edition that make it comparable to a different product than the standard edition.

In his 2013 dissertation, Lingkai Terence Teo examines the cost of capital associated with reward-based crowdfunding. To assess this, he compiles a list of assumed costs for different types of typical rewards. The part of the list applicable to this dissertation is as follows:

<table>
<thead>
<tr>
<th>Reward</th>
<th>Assumed value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dinner</td>
<td>$30 per head</td>
</tr>
<tr>
<td>Party</td>
<td>$30 per head</td>
</tr>
<tr>
<td>Postcard</td>
<td>$1</td>
</tr>
<tr>
<td>T-shirt</td>
<td>$25</td>
</tr>
<tr>
<td>Pre-existing commercial product or service</td>
<td>The retail price of the product or service</td>
</tr>
</tbody>
</table>

As I see no reason to deviate from these quite reasonable assumptions, I have used them as a basis for the reward values assumed in my dissertation. In case a reward consists of other merchandise not covered by this list, a valuation system similar to valuing the finished product is applied. Like in the case of the finished product, if a reasonably reliable estimate of any reward’s value cannot be produced, the project, as a whole, is excluded from the study. Also, for the sake of comparability between projects, the same alternative product is used as a price benchmark for projects that offer slightly customized versions of essentially the same product as rewards. So, for example, a keychain with the logo of project A on it is considered to have the exact same value as a keychain with the logo of project B on it.
It is worth noting that, unlike Teo, I have no ambition to assess the exact reward values, only a rough estimate of the level thereof. Therefore, any slight inaccuracies in the pricing is likely to have either a diminished effect or no effect at all to my results. Nonetheless, I recognize that this valuation system is not perfect; it is simply the best one available at the moment at a reasonable cost in terms of time and money.

\[ x_{9i} = \text{Average time to delivery:} \] The average time between the completion of the Kickstarter campaign and the estimated delivery of rewards. As with the previous variable, the average time to delivery is measured as the simple average of the estimated delivery times of the rewards of the various levels. The estimated delivery date found on Kickstarter is only expressed as month and year, so the exact delivery date is assumed to be the first day of the month in question. (Of course, any particular day of each month would have been an equally reasonable assumption – the first day was chosen because MS Excel, the spreadsheet program used to accumulate the data, automatically interprets a month-and-year date as the first day of the month in question.) Some rewards are promised to be delivered during the same month the campaign ends; these rewards are assumed to have a delivery time of zero. It is worth noting that since this data contains zeroes, no logarithmic transformation can be done without excluding a part of the sample in a way that skews the sample.

\[ x_{10i} = \text{Number of reward levels:} \] The number of reward levels (or tiers) the project has. This variable is introduced as an additional sign of effort and commitment on the part of the project creator: designing lucrative rewards and assessing their required contribution level requires additional work, and is, as such, interpreted as a sign of commitment to the project. Also, the inclusion of several reward levels may increase the chance of potential backers finding a reward they find appropriate, which may increase willingness among them to back the project.

4.1.3 Additional variables not applicable to all projects

Some of the independent variables can only be defined in cases where the project has at least one backer, or that fulfil some other criteria that not all projects fulfil. As such, they cannot be included in all models. These variables are introduced in this section.

\[ x_{11i} = \text{Average reward value for chosen rewards:} \] Same as the reward value variable above, with the exception that this variable is calculated as an average of the reward values of all reward levels with at least one backer, and each level’s value is weighed
based on its number of backers. As many projects also have backers who opt out of rewards altogether (and thereby effectively choose a reward value of 0), the denominator in the equation is still the total number of backers (as opposed to the number of backers who have chosen a reward). This gives the actual average value of reward obtained by each individual backer of a given project, which is a somewhat better indicator of whether or not the monetary value of rewards is actually a motivating factor in the decision-making process of potential backers than a simple average of the reward values.

\[ x_{12i} = \text{Average delivery time for chosen rewards} \]  

Same as the delivery time variable above, except weighed similarly as the average reward value for chosen rewards, based on the rewards backers actually choose. Again, this is done to indicate backer preferences better than a simple average of the delivery times of all available rewards for a given project.

### 4.2 Model diagnostics

As the logit model is not linear and is not estimated using Ordinary Least Squares (OLS), but rather the maximum likelihood method (ML), the standard array of model diagnostics associated with OLS is not applicable. I will, however, use the percentage of correct predictions, as well as pseudo-R² score to assess the goodness of fit of my models to the data and take this into account in my results.

As my data is cross-sectional, some diagnostic tests do not apply to the CLRM part of my study either. As there is neither a temporal, nor any other distinguishable dimension to the data, autocorrelation does not need to be tested for. Logarithmic transformations are done to the non-binary independent variables (except those containing zeroes) to induce normality, which should reduce problems with possible non-normality. Besides, as Brooks (2008, p. 164) points out, violation of the normality assumption for large sample sizes are is “virtually inconsequential”. As a result, the data must still be tested for heteroscedasticity and multicollinearity.

Heteroscedasticity can be tested for in a number of ways. Brooks (2008) suggests the Goldfeld-Quandt (1965) test, but for the sake of convenience, White (1980) test was
ultimately chosen for this study, as the econometrics program Gretl has this test built in. If heteroscedasticity is noticed, Gretl’s “heteroscedasticity robust standard errors” function will be used to mitigate the problem (if the form of heteroscedasticity, if any, was known, one could modify the variables to eradicate the problem, but this seems unlikely to be the case in practice).

As in all practical contexts, there is some correlation between the explanatory variables in the data. To find possible near multicollinearity, a correlation matrix is drawn and examined, as suggested by Brooks (2008, p. 172).
5 DATA

The data for this dissertation have been collected from Kickstarter.com. The data collection has been done in several increments, the first of which took place in June-July 2015 and the rest in September-October 2015. The data consists originally of 305 projects. However, five of them were cancelled by the project creators before the end of the campaign, and were subsequently excluded from the study. (It is worth noting that Colombo, Franzoni and Rossi-Lamastra, 2015, code these projects as failed. In my view, this would distort the data in my case, as some of these projects were doing well before the cancellation, looking as though they would probably reach their goal, and therefore were more likely to resemble successful than unsuccessful projects in terms of success-affecting characteristics.) Data on most of the variables considered in the study are readily available on the site. However, the assessment of the value of a certain reward, as well as the publicity the project has gained, if any, had to be done using external resources, such as the internet search engine Google.

As Kickstarter itself, to my knowledge, offers no way to browse ended projects as a list, browsing ended projects, where all data was available immediately, was, in practice, not a viable option. Kickstarter does, however, retain information on ended projects – they simply have to be searched for by name individually or one has to know the exact URL of the project page.

As such, by far the most convenient method of data gathering became choosing current Kickstarter projects as data – since they can be found on the Kickstarter site without any previous knowledge about them – and following their progress.

The projects were first arranged by their end date (so that the project in a given category ending the soonest will be displayed first, the second soonest second and so forth). This was done for two reasons.

First, the arranging the projects in a chronological order effectively ensured a fairly random sample of projects. As nothing in previous research or otherwise available data suggests that projects that are started close to each other share an unusual number of characteristics (save for the obvious temporal correlation), this approach became an easily facilitated way of randomizing the sample. Of course, as the ordering was not completely random, some bias was, by definition, introduced. This is unlikely to have a practical significance, however, partly due to the aforementioned lack of evidence for
temporally correlated projects sharing characteristics, and partly due to the fact that
the data collection was done over an extended period of time, and the exact dates were
determined by factors that were essentially random, so any unlikely bias of actual
importance is likely to affect only a small subset of the sample.

Second, as some of the data required for this dissertation could only be obtained from
finished projects, but finished projects could not be browsed as a list, the easiest way to
obtain this data was to choose a project close to its end date, save its URL and revisit it
as soon as it was finished.

The details of these projects were then gathered from the project’s Kickstarter page and
the occasional external resource, primarily using a simple Google search. This was the
primary stage of data collection. At this point, all data could be collected except for the
following:

- The final amount of money collected by the project
- The final number of backers overall
- The final number of backers on a given reward level
- The final number of comments posted on the project’s page (as background
  information, not an independent variable)

For this reason, at the start of each data collection session, I revisited the projects
inspected during the previous session, collecting the remaining pieces of data.

Like Mollick (2014) did, I have restricted the research to projects with stated
fundraising goals of over $5,000, since projects with very low stated goals are unlikely
to follow the same dynamics as those with substantially higher goals. I did not,
however, set an upper limit. This is because Mollick’s upper limit of $1 million seems
no longer to be an upper limit above which projects can be considered “not serious”.
For example, the computer role-playing game Pillars of Eternity, financed through
Kickstarter, with the initial stated goal of $1.1 million, managed to raise nearly four
times that, and was released successfully in March 2015. (Metacritic.com,
Kickstarter.com) However, projects with a goal above $1 million are a rarity, and in
fact, due to the restrictions related to the approximate quantifiability of reward values,
neither of the two encountered during data collection made it to the final dataset.
5.1 Descriptive statistics

The final dataset consists of 300 projects, 163 of which are in the Technology category and 137 of which are in the Games category. 249 of them received at least one backer (120 in the Technology category and 128 in the Games category), and 225 of them received at least one backer that chose a reward (110 in the Technology category and 115 in the Games category). In this section, I will present my dataset in general. Averages of binary variables represent the percentage of projects that fulfil the criteria in question. Only the standard deviations of non-binary variables are presented.

Table 5.1: Averages and standard deviations of the full dataset

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Success</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>Percentage of goal achieved</td>
<td>0.60</td>
<td>1.51</td>
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<tr>
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<tr>
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<tr>
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</tr>
<tr>
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<td>543.51</td>
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<tr>
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</tr>
<tr>
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<td>Average time to delivery</td>
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<td>152.27</td>
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Table 5.2: Averages and standard deviations of Technology projects

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<td>Standard deviation</td>
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<tr>
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<tr>
<td>Percentage of goal achieved</td>
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<td>1.38</td>
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<td>Average reward value</td>
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<td>No. Of reward levels with backers</td>
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<td>5.51</td>
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<td>Average chosen reward value</td>
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</tr>
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<tr>
<td>Average chosen delivery time</td>
<td>172.84</td>
<td>183.08</td>
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Table 5.3: Averages and standard deviations of Games projects
As is apparent from the figures above, Games projects in the dataset have a significantly higher success rate than Technology projects: approximately a third of Games projects managed to accumulate their goal amount, compared to only a fifth of Technology projects. These results very closely resemble the official statistics published by Kickstarter, which encompass all projects: according to them, Games projects have a 32.89% success rate, while Technology projects have a success rate of 20.18%. (Kickstarter.com) In line with this, Technology projects gathered on average 20801.09 dollars (or an equivalent sum), while Games projects gathered on average 34458.14 dollars (or an equivalent sum). Most variables, however, do present broadly similar behavior in both categories, with the exception of delivery times, both in general and those chosen by the backers: the Games category had substantially longer delivery times in both cases.

It is also worth noticing that Technology projects, on average, have much more ambitious goals: their average goal is 60,336.93 Dollars, compared to the only 41,536.02 Dollar average goal of Games Projects. However, as is evident from figure 4.1.1, which covers projects with a goal up to $100,000 (90.7% of all projects), this average is clearly above the median of $12,000 for Games projects and $23,079 for Technology projects. Goals are concentrated at the lower end of the spectrum, with the mode for Games projects being $10,000 and for Technology projects $5,000.

![Figure 5.1: Frequency distribution of project goals up to $100,000](image)
The total sums pledged to each project are even more prominently tilted towards the lower end of the spectrum, with 286, or 95.3% of all total pledged amounts falling within the figure 4.1.2, which only covers total collected sums up to $100,000. 235, or 78.3 percent of all projects, fall within the lowest frequency bin of $0-10,000.

![Frequency of total sums pledged](image)

*Figure 5.2: Frequency distribution of total sums collected up to $100,000*

It is also worth noting that the vast majority of projects either acquire all the funding they seek or almost none at all, with very few projects falling in between these two extremes. Figure 4.1.3 shows the distribution between the different levels of percentages of goal achieved by all projects.
Figure 5.3: Frequency of percentages of goal achieved
6 RESULTS

6.1 Model diagnostics

6.1.1 Heteroscedasticity
As the classical linear regression model used in the second part of the study assumes no heteroscedasticity, White’s test was run on the residuals of each CLRM regression to see if heteroscedasticity-robust standard errors are necessary, using the statistics program Gretl’s automatic White’s test for heteroscedasticity function. P-values of less than 5 % were interpreted as evidence of heteroscedasticity. Models 11, 13, 16, 17, 18 and 20 were deemed to contain heteroscedasticity, and heteroscedasticity-robust standard errors were thus used.

6.1.2 Multicollinearity
The correlation matrix used to expose possible multicollinearity can be found in Appendix 1. The matrix shows no significant correlation between the independent variables with the rather obvious exceptions of average reward value and chosen reward value, and average delivery time and chosen delivery time. As both of these draw from the same, very limited pool of observations for each project (the reward values and their associated delivery times, respectively), it is to be expected that these correlate highly with each other.

As such, regressions that use one of the variables of each collinear pair can’t use the other. Since only the average reward values and estimated delivery times of all reward levels of projects are known beforehand (final data about which reward levels are ultimately chosen can only be extracted once the project has completed its campaign), these are of more interest from the point of view of my study. Therefore, the total averages are considered in most of my regressions, with only models 3, 4, 13 and 14 considering the chosen rewards and/or their delivery times.

6.2 Omitted variables
Initially, the models were run with all the variables mentioned earlier included in them. However, after this first run, the variables Video, FBF dummy, Delivery time and Chosen delivery time were found to have statistically significant coefficients in none of the models proposed. As such, these were omitted from the models presented in the next chapter.

6.3 Logit and CLRM models

The results of the logistic regression models are presented in figure 6.1. Each model is not written down here separately, but the logic remains the same in all models: each model in the same table has the same dependent variable. The coefficients of the constant and all independent variables included in a particular model are presented in the table. If a particular field is empty, it means that the variable in question was not included in that model.

Each dataset had two regressions run on it. First, a larger multivariate regression which considered all the applicable independent variables was run. After this, another, smaller multivariate regression was run. In the second regression for each dataset, only independent variables that were determined to be statistically significant by the first regression, and the constant, were included. The pseudo $R^2$ values and percentages of correct predictions values for the logit models, and $R^2$ values for the CLRM models are presented in each case. This was done so that the effect of leaving out the statistically nonsignificant variables on the statistical significance of the significant variables and the overall goodness of fit of the models to data could be observed.

It is easy to see that the overall goodness of fit statistics are not altered very significantly with the removal of statistically non-significant variables. The largest drop in pseudo $R^2$ and percentage of correct predictions when doing so (~0.02 and 2.9, respectively) are experienced in models models 7 and 8, which consider Technology projects, and 5 and 6, which consider Games projects, respectively. Same goes for CLRM models, where the largest drop in $R^2$ when omitting variables is 0.02, experienced in Technology. This indicates that the variables for each dataset that are not statistically significant are not crucial to the overall goodness of fit of each model.

In most cases, the omission of non-significant variables does not result in large changes in the significance or coefficient of the variables deemed significant by the first model, either. As such, the smaller models can be considered more parsimonious than the
larger ones, since they achieve almost the same of goodness of fit and otherwise very similar results with far fewer variables.

The Logit models exhibit more statistically significant independent variables than the CLRM ones. It is worth noticing that the logit model, by nature, fits this type of data exceptionally well compared to the other model options. Due to the fact that most projects acquire either a very small percentage of the funding they seek or all of it and beyond, with very few projects falling between these extremes, a binary model is a rather obvious choice for this dataset.

The pseudo $R^2$ values for the different models in this dissertation are generally around 0.5, indicating that the models fit the data reasonably well. Despite this, it is also apparent that many aspects of the phenomenon are not captured by my variables, leaving room for further studies on the subject.
### Table 6.1: The results of the logistic regression models

<table>
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<th></th>
<th>Constant</th>
<th>Ln(Goal)</th>
<th>Ln(duration)</th>
<th>Staff pick</th>
<th>Quick update</th>
<th>Publicity</th>
<th>Ln(FBF)</th>
<th>Reward value</th>
<th>Ln(No. of reward levels)</th>
<th>Chosen reward value</th>
<th>McFadden’s pseudo R²</th>
<th>Percentage of correct predictions</th>
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<td>1.00***</td>
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Dependent variable: Success (binary variable)

*p< 0.1 **p<0.05 ***p<0.01
Table 6.2: The results of the classical linear regression models

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<th></th>
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<th>Ln(duration)</th>
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Dependent variable: Percentage of goal achieved

*p<0.1 **p<0.05 ***p<0.01
The staff pick and quick update variables seem to be the most consistently statistically significant independent variables in the models. Each of these is found to be statistically significant in every single model, in most cases on the rather strict 1% significance level. Also the goal of the project had a significant negative correlation with its success and the percentage of its goal it achieved in a majority of cases.

Of the variables introduced specifically for this dissertation, the number of reward levels predicted success the most consistently within the logistic regression models, but failed to perform as well in the CLRM models, where it was only a statistically significant predictor of success for Technology projects. Average reward value was also a fairly consistent statistically significant predictor of success, having statistical significance in most of the models it was introduced to on both the logit and CLRM parts of the study. In addition, the chosen reward values had a statistically significant positive correlation with the success of the study in the logit model.

At the other extreme, the introduction of a video could not in any model be found to have a statistical significance for the success of a project or the percentage of its goal it manages to achieve. Same goes for whether or not the project had Facebook connected to it. Interestingly, however, those projects that had Facebook connected to them exhibited a statistically significant sensitivity to the amount of Facebook friends the project’s creator has in logit models.

### 6.4 Sensitivity analysis

As the previously established cutoffs of 75% and 125% for reward values 2 and 3, respectively, had to be made on a subjective basis in the absence of theoretical reference, they may bias the results. In this section, other cutoffs are tested to see if changing the cutoff affect results.

The regressions presented in 5.2 are repeated using the cutoffs of 50%/150%, 60%/140% and 90%/110%. This test reveals that no major changes in the results occur in the coefficients or their significance when the cutoff is changed. However, it is also worth noticing that an increase of the lower cutoff (and the corresponding decrease of the upper cutoff) does fairly consistently lower the coefficient and decrease statistical significance, if present. However, in no instance does the coefficient lose a statistical significance present on the 75% level altogether when the cutoffs are changed, and only decreases in significance in models 5 and 20.
It is also worth noticing that in this sensitivity analysis, even the CLRMs of all projects and projects with backers start exhibiting statistically significant sensitivity to reward value when the cutoff is loosened to 50%/150% or 60%/140% from the 75%/125% level.

Other variables’ coefficients or significance are not changed with the altered definitions of the reward value variable in a significant fashion. Slight changes occur, as is to be expected in any restructuring of a regression model, but nothing that would necessitate further investigation. As such, independent variables other than the (chosen) reward value are excluded from the tables below. Each model is, with the exception of the reward value cutoffs, identical to the model of corresponding number in the results tables above. For the sake of comparison, however, the full coefficients and their significances in the logistic regression models at the 50%/150% reward value cutoffs are presented in Appendix 2.

**Table 6.3: Sensitivity analysis of the Logarithmic Regression models**

<table>
<thead>
<tr>
<th></th>
<th>Reward value 50%/150%</th>
<th>Chosen reward value 50%/150%</th>
<th>Reward value 60%/140%</th>
<th>Chosen reward value 60%/140%</th>
<th>Reward value 90%/110%</th>
<th>Chosen reward value 90%/110%</th>
<th>Reward value 75%/125%</th>
<th>Chosen reward value 75%/125%</th>
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</thead>
<tbody>
<tr>
<td><strong>All projects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1</td>
<td>0.91***</td>
<td>0.86***</td>
<td>0.56**</td>
<td></td>
<td></td>
<td></td>
<td>0.70**</td>
<td></td>
</tr>
<tr>
<td>Model 2</td>
<td>0.69**</td>
<td>0.84***</td>
<td>0.55**</td>
<td></td>
<td></td>
<td></td>
<td>0.69**</td>
<td></td>
</tr>
<tr>
<td><strong>Projects with backers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 3</td>
<td>0.64**</td>
<td>0.60**</td>
<td>0.47**</td>
<td></td>
<td></td>
<td></td>
<td>0.57**</td>
<td></td>
</tr>
<tr>
<td>Model 4</td>
<td>0.64***</td>
<td>0.60**</td>
<td>0.48**</td>
<td></td>
<td></td>
<td></td>
<td>0.57**</td>
<td></td>
</tr>
<tr>
<td><strong>Games projects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 5</td>
<td>1.65***</td>
<td>1.62***</td>
<td>0.92**</td>
<td></td>
<td></td>
<td></td>
<td>1.32***</td>
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</tr>
<tr>
<td>Model 6</td>
<td>1.63***</td>
<td>1.58***</td>
<td>0.92**</td>
<td></td>
<td></td>
<td></td>
<td>1.28**</td>
<td></td>
</tr>
<tr>
<td><strong>Technology projects</strong></td>
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<td></td>
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<td></td>
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<tr>
<td>Model 7</td>
<td>0.46</td>
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<td>0.38</td>
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<td>Model 8</td>
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<tr>
<td><strong>Projects with Facebook connected</strong></td>
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</tr>
<tr>
<td>Model 9</td>
<td>0.84</td>
<td>0.81</td>
<td>0.5</td>
<td></td>
<td></td>
<td></td>
<td>0.67</td>
<td></td>
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<tr>
<td>Model 10</td>
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<td></td>
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</tr>
</tbody>
</table>

*Dependent variable: Success (binary variable)*

*p<0.1 **p<0.05 ***p<0.01
Table 6.4: Sensitivity analysis of the CLRM

<table>
<thead>
<tr>
<th>Model</th>
<th>Reward value 50%/150%</th>
<th>Chosen reward value 50%/150%</th>
<th>Reward value 60%/140%</th>
<th>Chosen reward value 60%/140%</th>
<th>Reward value 90%/110%</th>
<th>Chosen reward value 90%/110%</th>
<th>Reward value 75%/125%</th>
<th>Chosen reward value 75%/125%</th>
</tr>
</thead>
<tbody>
<tr>
<td>All projects</td>
<td>0.20**</td>
<td>0.23**</td>
<td>0.16</td>
<td>0.15</td>
<td></td>
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</tr>
<tr>
<td>Model 11</td>
<td>0.21*</td>
<td>0.26**</td>
<td>0.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Projects with backers</td>
<td>0.28***</td>
<td>0.27***</td>
<td>0.23</td>
<td>0.18</td>
<td></td>
<td></td>
<td></td>
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<td>Model 13</td>
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<tr>
<td>Games projects</td>
<td>0.45***</td>
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<td>0.45***</td>
<td>0.39**</td>
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<tr>
<td>Model 15</td>
<td>0.45**</td>
<td>0.50**</td>
<td>0.45**</td>
<td>0.40**</td>
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<tr>
<td>Technology projects</td>
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<td>0.05</td>
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<td>0</td>
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</tr>
<tr>
<td>Model 17</td>
<td>0.30**</td>
<td>0.34***</td>
<td>0.33***</td>
<td>0.28**</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Projects with Facebook connected</td>
<td>0.29**</td>
<td>0.32**</td>
<td>0.31*</td>
<td>0.29**</td>
<td></td>
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<tr>
<td>Model 19</td>
<td>0.28**</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Model 20</td>
<td>0.28**</td>
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</tr>
</tbody>
</table>

*Dependent variable: Percentage of goal achieved
*p< 0.1 **p<0.05 ***p<0.01

6.5 Inter-variable interactions

To further examine the dynamics of a crowdfunding venture, regressions are run with the previously explanatory variables as the dependent variable. However, since some of the variables are known at the start of the campaign (reward values, goal etc.) and some are not (staff pick, publicity etc.), not all variables can be regressed against the others. As such, variables are only regressed against other variables whose values could have been known at the time these variables were set. It is noteworthy that the order in which project creators decided on the variables that are known at the start of a campaign likely varies on a case-by-case basis. Therefore, these results should be interpreted as a study of general interconnection, rather than suggesting any form of direct causality. Then again, when considering whether, for example, publicity affects a project’s chances of being staff picked or vice versa, both hypotheses are plausible – and indeed, are supported by the results. The causal relationship may even be two-fold, with each increasing the chance of the other.
The results are presented in the table below. The far left column indicates the dependent variable of each model, whereas the uppermost row indicates the explanatory variables. As previously, an empty cell indicates that a variable was not included in a model. The two last columns on the right side of the table indicate the R² or McFadden’s pseudo R² statistics (whichever was applicable, considering the model used) and the model used, respectively. Model diagnostics were run and corrections made where applicable.

Table 6.5: Inter-variable interactions

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>Ln(Goal)</th>
<th>Ln(Duration)</th>
<th>Staff pick</th>
<th>Quick update</th>
<th>Publicity</th>
<th>Reward value</th>
<th>Ln(No. of reward values)</th>
<th>(Pseudo) R²</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(Goal)</td>
<td>8.93***</td>
<td>0.36</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.18**</td>
<td>0.04</td>
<td>0.02</td>
<td>CLRM</td>
</tr>
<tr>
<td>Ln(Duration)</td>
<td>3.12***</td>
<td>0.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.02</td>
<td>0.02</td>
<td>0.01</td>
<td>CLRM</td>
</tr>
<tr>
<td>Staff pick</td>
<td>-7.75</td>
<td>0.15</td>
<td>0.16</td>
<td></td>
<td></td>
<td></td>
<td>1.19**</td>
<td>1.50***</td>
<td>0.59*</td>
<td>Logit</td>
</tr>
<tr>
<td>Quick update</td>
<td>-0.90</td>
<td>-0.02</td>
<td>-0.78*</td>
<td></td>
<td></td>
<td>0.71</td>
<td>0.79***</td>
<td>1.15***</td>
<td>0.23</td>
<td>Logit</td>
</tr>
<tr>
<td>Publicity</td>
<td>-12.28***</td>
<td>0.34*</td>
<td>0.91</td>
<td></td>
<td></td>
<td></td>
<td>0.34</td>
<td>1.30***</td>
<td>0.31</td>
<td>Logit</td>
</tr>
<tr>
<td>Reward value</td>
<td>1.19**</td>
<td>-0.07</td>
<td>0.09</td>
<td></td>
<td></td>
<td></td>
<td>0.24***</td>
<td>0.09</td>
<td></td>
<td>CLRM</td>
</tr>
<tr>
<td>Ln(No. of reward values)</td>
<td>0.61</td>
<td>0.02</td>
<td>0.12</td>
<td></td>
<td></td>
<td></td>
<td>0.31***</td>
<td>0.08</td>
<td></td>
<td>CLRM</td>
</tr>
</tbody>
</table>

*p<0.1 **p<0.05 ***p<0.01

As is evident from the table, several interactions between variables are statistically significant, but it is noteworthy that, with the exception of publicity, which can be assumed to partially follow the same dynamics as the project’s ultimate success, most of the equations have R² or pseudo R² values of less than 0.3, indicating that a quite small percentage of them is explained with the help of the other variables.
7 DISCUSSION

In this section, I will discuss the questions about the factors of a successful campaign, as well as the results of earlier studies, in the light of my results.

7.1 What drives the success of a reward-based crowdfunding campaign?

7.1.1 Does the backer calculate?

From a finance standpoint, one of the most important questions that this thesis aims to answer, which was also posed by my supervisor in our very first meeting, is whether or not the expected rewards for backing a project can be considered assets. The IFRS foundation and IASB (2013) define an asset as “a resource controlled by the entity as a result of past events and from which future economic benefits are expected to flow to the entity”. In this strict definition, all claims to rewards that have nonzero monetary value are clearly considered assets.

However, a rational investor should try to invest in assets that have maximal Present Value, and positive Net Present Value, that is, the present value of the expected payoff should exceed, or at least equal the price the investor has to pay to acquire the asset. (Fisher 1907, p. 150, Ross 1995)

In the case of Kickstarter projects as investments, it is worth noting that estimating the exact value of the asset is extremely hard. Also, there is no established system of enforcing reward payments, which, in and of itself, creates a very a high risk level. Furthermore, with an average chosen reward value of 1.06, clearly lower than the required investment to obtain it even without discounting, one can safely conclude that financial gain is not the main motivator of the average Kickstarter backer.

However, it is also worth noting that average reward value did, in fact, have a statistically significant positive impact on the success of projects, indicating that while it may not be a primary motivator, calculation of personal gain does play a role in explaining the phenomenon of the Kickstarter backer. It is also noticeable that in the logit models that had the average value of rewards actually chosen by backers as an independent variable also found it to have a positive and statistically significant coefficient. This seems likely to be a result of potential backers, given the choice, being more willing to back projects if they offer
the possibility of higher compensation – an option which is subsequently also utilized by the potential backers.

It is worth noting that that the projects examined for this study gathered a total of 116,918 backers. Even if it is likely that some backers did back more than one project, this still indicates a very large amount of different backers, with their motivations ranging from the demonstrably altruistic (as many backers chose to forgo reward altogether) to those that obviously involved a fair deal of calculation (as evidenced by the many instances of backers rushing to a limited “early bird” discounted unit of the eventual product).

However, as the delivery time variable time and again failed to play a significant role in the success of a project or the percentage of its goal it managed to achieve, and its coefficient was invariably extremely close to zero, one has to conclude that the average backer is not very sophisticated in considering the time-value of money.

As a conclusion, one can say that at least some investors do calculate to a degree, but that other factors are definitely needed to capture the extent of the phenomenon of a successful reward-based crowdfunding project.

### 7.1.2 Signals of quality and preparedness, and their role

While not formally defined as such, becoming Staff picked by Kickstarter may well be one of the most important signs of quality a project can exhibit. As Kickstarter employees go through a myriad of projects on a daily basis, their assessment of a project is almost certainly of more value than an average person’s. Therefore, it is no wonder that becoming Staff picked was one of the most reliable predictors of success for a Kickstarter project. However, this is not a simple matter of quality indication, since becoming a Staff pick also increases a project’s visibility on the page (a Staff picked project is more likely to be shown to a random visitor within its category if default arranging terms are not altered). Therefore, one cannot really conclude in which proportion the variable indicates quality and in which it increases the chances of success through other means. Nonetheless, it is very likely that the truth is some combination of the two, and the proportion may well vary from project to project.

The project page including a video was not found to have a statistically significant positive impact on a project’s success, even if its coefficient was, in most cases, found to be positive. This is likely due to the fact that as Kickstarter urges all projects to include a video on their page, most project creators take the hint, and almost 70% of all project pages nowadays include a video. Due to this, including a video is probably no longer a reliable indicator of a
project’s quality. It is also possible that the effect is present, but so slight that a larger sample would be required to reliably verify its existence.

The quick update variable was found to be of statistical significance in most cases. While it is apparent that this variable does signal a creator’s commitment to the project, as pointed out by Mollick (2014), it is also worth noticing that a number of quick updates do not comment on the project itself, but rather the number of pledges it has managed to gain in so short a time. Therefore, the relationship between quick updates and the project’s success may be at least partially inverse: project creators update the page to thank the backers for their already committed support, rather than providing additional info that may encourage further backers. Once again, it is likely that the truth about the effect of quick updates on a project’s success is some composite of these two factors, and possibly other, for the time being unknown ones.

The variable of number of reward levels was a surprisingly good predictor of success for a project – it was both statistically significant in all logit models and had a high coefficient – and in reflection, this does make sense for several reasons. First, it is likely that a project with a great number of reward levels has a very committed creator (or, more likely, a team of them), as laying out the plans to create and deliver a number of different rewards is time-consuming and requires effort. This makes the number of reward levels yet another indicator of a project creator’s preparedness and commitment, and, by extension, that of the project’s quality. Second, with many reward levels from which to choose, backers are more likely to find themselves a reward that, in their view, is adequate compensation for the sum they pledge to back the project.

7.1.3 Publicity and social networking

The publicity variable was found to have a statistically significant positive effect on projects in general. This does, however, beg the question of causality: do potential backers generally find interesting projects via their publicity, or do projects that gain a lot of backers get more easily noticed by the media during the campaign time? Since my data about publicity is not confined to publicity prior to the campaign, this question cannot be definitively answered, and this leaves therefore some room for interesting further research.

The upside of my method, however, is that it captures effects that the aforementioned alternative approach would not. First, media may well play a role in facilitating a snowball effect around eventually successful campaigns: projects off to a good start are probably more likely than others to draw attention by the media, which in turn alerts the public, and thereby
more potential backers, to their existence. Second, some projects that are close to completing their goal, but not quite there, do experience a surge of backers near their stated deadline. A model that excludes publicity gained during the campaign would fail to account for the media’s role in this effect. Also, it is worth noticing that some projects have considerable planning behind them already before the Kickstarter campaign, and may have attracted media attention a long time before ever getting to the Kickstarter phase, especially if the creators are well-known within their field or in general. An article published a year before the campaign is likely to have a smaller impact on the success of a project than one that is published while the project’s campaign is ongoing.

None of the models could find a significant link between linking a Facebook profile to a project and its chances of success, one way or the other. This is perhaps to be expected: while one could theoretically assume Facebook to be a good method of grassroots marketing, nothing stops creators from sharing their project on Facebook even if their accounts are not directly linked to the project. Furthermore, while Facebook connection in the project may serve as an indicator of at least rudimentary social networking skills on the part of the creator, it may be fair to assume that anyone willing to use Kickstarter – which itself has some features of a social network – does have basic knowledge of internet-based social networking. However, it is also worth noting that projects that did have Facebook connected to them did exhibit a positive correlation between the amount of Facebook friends of the creator and the project’s success. This indicates that the social network size of the creator does play a role in getting the project some much-needed attention.

7.1.4 Project set-up

The goal of the project was one of the most reliable indicators of its success: a lower goal did tend to lead to a significantly higher likelihood of successful funding. This is only natural: a project that needs less funding has a considerably easier time obtaining it from a large group of backers. This leads to a very concrete practical application for project creators: it is reasonable to only ask for the minimum amount required to be able to start production. Another implication is that crowdfunding should not, if possible, be used in isolation: if any portion of the required starting capital can be raised using other means, this also increases the chances of a crowdfunding campaign successfully raising another part (due to the lower required goal).

Only the CLRM models of games projects and projects with Facebook connected found the duration of the project to have a statistically significant impact on the percentage of its goal it
manages to meet. These models, as well as a vast majority of the non-significant ones, however, found its coefficient to be, perhaps slightly unexpectedly, negative. This result is likely due to the fact that it is harder to keep a buzz going around projects that run for a long time. Therefore, longer projects may, for example, fail to gain a surge of backers towards the end. Also, it is worth noting that this effect was also observed by Mollick (2014), who attributed it to a lack of confidence on the creator’s part – also a valid explanation to this slightly counter-intuitive finding. It is also possible, however, that projects with longer (or, conversely, shorter) funding time share some common characteristic not captured by my model, which has a negative (or, in the case of shorter campaign length, positive) impact on achieving a funding goal.

7.1.5 Games vs. Technology

The two different categories exhibited broadly similar behavior, with the only major difference being the effects of reward value and publicity on the project’s success, which were found to be statistically significant for games but not for technology. The greater impact of the reward value is likely attributable to a less diverse set of projects within the Games category. The Technology category included projects ranging from novel smartphone applications to portable wind turbines, which were more difficult to price accurately, and more often had elements of “common good” that could make backers more willing to back the projects for altruistic reasons than Games projects. The Games category, on the other hand, included mostly projects where the end product was a comparatively standard entertainment product, and as such, far easier to price and less likely to be supported out of the kindness of backers’ hearts – thereby leading to a more calculating set of backers.

The different role of publicity between the categories is likely to be explained by the amount of prominent internet-based media outlets that focus solely on games. The abundance of these outlets makes it easier for a promising game project to gain publicity in the first place, and their large following makes it easy to steer potential backers towards projects they find interesting. There is no such devoted media around the more diverse technology projects, making it harder for them to gain publicity and benefit from it.

7.2 Comparison to previous studies

In this section, I compare my results to Mollick’s (2014) and discuss the study of Belleflamme, Lambert and Schwienbacher (2014) in the light of my results. I do not compare
my results to those of Colombo, Franzoni and Rossi-Lamastra (2015), however, due to my study being more complementary than comparable to theirs.

### 7.2.1 Mollick (2014)

When comparing my results to Mollick’s, it is first necessary to note that Mollick uses odds ratios, while my study uses log-odds ratios, so the coefficients are not directly comparable. A negative coefficient in my study corresponds to a coefficient of less than 1 in Mollick’s. It is also worth noting that Mollick never specifies the type of pseudo R² he uses, so his pseudo R² values may also be incomparable to mine. However, as Veall and Zimmermann (1996) point out, McFadden’s pseudo R² is probably the most commonly used pseudo R². Another difference worth noting is that I did not, partially due to my smaller sample and partially due to a slightly different focus, go as deep into the size of the project creator’s social networks as Mollick did. Also worth noting, on the other hand, is that my study included variables that Mollick’s did not.

In general, my results were largely similar to those of Mollick’s. The Featured variable Mollick used was replaced by Staff pick in my study, but they are largely similar in effect, and both were found to have a positive impact on the success of a Kickstarter campaign. My study also agreed with Mollick’s on the negative impact of a higher project goal on the project’s chances of success, as well as the fact that a quick update correlated with a higher chance of success (although I am somewhat more hesitant to attribute this to the preparedness of the founder than Mollick was). My study also replicates the seemingly counterintuitive finding by Mollick that a longer project duration leads to a diminished chance of success.

While Mollick also finds a positive correlation between including a video on the project page and its chances of success, this study fails to replicate this effect. It is quite possible that the dynamics have changed in this regard – but it is also possible that, as Mollick’s study includes more categories than mine, the effect only exists in certain categories included in his study that are not included in mine.

Finally, it is worth noting that comparing my R² values, which revolve around or slightly below 0.5, to Mollick’s (2014), which were uniformly between 0.1 and 0.18, reveals that my models seem to capture a considerably larger part of the phenomenon. It bears repeating, however, that it is not exactly clear if both studies use the same pseudo R². Veall and Zimmermann (1996) do point out, however, that McFadden’s pseudo R² does actually produce lower values than some of the alternatives, making it somewhat more likely that this
difference is not explained to any large extent by the potentially different pseudo $R^2$ statistics.

### 7.2.2 Belleflamme, Lambert & Schwienbacher (2014)

As the study of Belleflamme, Lambert and Schwienbacher is not of the empirical kind, a direct comparison of results is naturally not possible. My study does, however, offer some insight into how realistic their assumptions are.

First, it is worth pointing out that many projects offer community benefits in one form or another, but their monetary value is often questionable at best. Typically, backers are sent updates about the project’s progress and are allowed to comment on the Kickstarter page, but these hardly carry any concrete value in the traditional sense. This effect is heightened in cases that use the pre-ordering model: for the pre-ordering crowdfunder, the extent of the community benefits was typically restricted to being able to comment on the campaign’s Kickstarter page and getting to read the backers-only updates on the project. Then again, community benefits are, in their model, assumed to come at no cost to the project creator.

Furthermore, their outcome that, in the presence of nonzero community benefits, crowdfunders always pay more than regular customers, is demonstrably incorrect (or, at the very least, is very likely to be so): projects fairly often offer the eventual product as a reward for a pledge lower than the stated intended retail price, even in the presence of community benefits. However, this is mostly a problem of a perhaps too strict interpretation they give to their own results: statements containing “always” can be universally proven false with one example to the contrary. If we interpret the result in a slightly less strict manner, we could state that on average crowdfunders pay more in the presence of community benefits. Since community benefits are, to a degree, always present in Kickstarter, this statement can be examined in the light of my data, and does seem to gain some support from it. Even though the reward value was found by many models to play a role in the success of a campaign, it is worth noting that the average reward value, even for successful campaigns, was considerably below 2, indicating precisely that crowdfunders generally end up paying more, on average, than regular customers. Then again, not all projects offer the end product as a reward, so this interpretation is only indicative, not definitive.

One point of view not explicitly considered by Belleflamme, Lambert and Schwienbacher is that in some cases, crowdfunders may actually pay a non-monetary price for their participation in the funding process in the form of making an at least partially uninformed
consumption decision. Also, one could view the risk associated with the uncertainty of the delivery of a reward as a non-monetary price the crowdfunder pays for his participation.
8 CONCLUSION

This study has shed light on some so far unanswered questions relating to the area of reward-based crowdfunding. On the basis of my results, it is not unreasonable to conclude that this phenomenon follows an easily-understood logic in many aspects, but that much of it must be explained using rather intricate psychology rather than straightforward mathematical modelling.

8.1 Suggestions for further research

For the time being, several aspects of reward-based crowdfunding still remain undiscovered. To better understand the factors that affect the success of a campaign, more variables must be discovered. For example, some way to model herd mentality and measure the likelihood of a project being noticed by backers would provide interesting insight.

This dissertation has focused on the categories of Technology and Games, so whether or not the results can be generalized to other kinds of projects is so far unknown. A study with broadly the same method and variables as this one that includes these categories would provide valuable insight into the overall dynamics of reward-based crowdfunding. Naturally, as this type of data is very time-consuming to collect, it would require more time than I have had, or alternatively a larger research team.

Furthermore, the cost of capital associated with reward-based crowdfunding is, at the time of writing, an almost complete unknown. Of course, in theory, the cost may be close to zero (as the rewards may be completely devoid of monetary value), but my results show that opting for this reduces the chances of success. A detailed analysis of the optimal balance between the cost of capital and likelihood of success would be a very interesting topic of research, with obvious practical implications. This would require a more precise method of quantifying the monetary value of individual rewards than the one used in this dissertation, however.

Although it is noteworthy how similar the applicable parts of my results are to Mollick’s, it may still be the case that the dynamics of crowdfunding are evolving, and therefore it would be interesting to repeat this study in, say, five years’ time, or even sooner.

8.2 Final remarks
As a young method of financing in its current form, scholarly knowledge on reward-based crowdfunding is understandably scarce for the time being, but it will undoubtedly increase in the following years, especially if the current trend of increasing popularity that crowdfunding is enjoying continues. As we continue to expand this knowledge on the subject, small businesses and start-ups will become better equipped to utilize this form of financing and bring forth new innovations that might otherwise never see the light of day.

As Aristotle (a 1999 translation) put it: “the many are better judges than a single man of music and poetry; for some understand one part and some another, and among them they understand the whole”. The same may well apply to the innovations of today.
9 SVENSK SAMMANFATTNING

9.1 Inledning


I dagens läge saknas ännu entydiga akademiska definitioner på olika typer av crowdfunding, men många studier och akademiska artiklar delar crowdfunding grovt i fyra olika kategorier (vars benämningar varierar): donationsmodellen, lånmodellen, belöningsmodellen samt investeringsmodellen. (Mollick 2014, Bouncken, Kromonek och Kraus 2015 m.fl.)


Lånemodellen liknar i stora drag traditionell lånefinansiering. I denna modell erbjuder stödjare projektet finansiering i form av små lån som betalas tillbaka med en viss ränta. Största skillnaden mellan denna modell och traditionell lånefinansiering är tillgängligheten: lånebaserad crowdfunding är lätt tillgänglig till individuella investerare, som ofta inte har likadana möjligheter att ge ut traditionella lån.

Den viktigaste modellen från denna avhandlings synpunkt är belöningsmodellen. Modellen går ut på att i stället för en monetär belöning, vilket förväntas av stödjare i fallet av lånemodellen och investeringsmodellen (vilken presenteras sist), belönas stödjare på något konkret men icke-monetärt sätt. Dessa belöningar varierar från mycket små till enorma, och beror typiskt på bidragets storlek. En typisk belöning är den slutliga produkten, vilken ofta
erbjuds till stödjare till ett billigare pris än det förväntade detaljhandelspriset, vilket medför att stödjare som vill ha den slutliga produkten kan drivas av kalkylering. Många stora och.synliga crowdfundingwebbsidor följer denna modell, bland annat Kickstarter, som är den primära datakällan för denna avhandling.


Det är värt att märka att dessa kategorier inte är absoluta. Projekt kan ha drag av flera former av crowdfunding: till exempel många projekt på Kickstarter följer delvis donationsmodellen och delvis belöningsmodellen.

I och med att denna avhandling koncentrerar sig på crowdfunding av belöningsmodellen, kommer termen crowdfunding att användas synonymt med denna typ av crowdfunding om inget annat näms.

9.1.1 Syfte

De grundläggande mekanismerna av belöningsbaserad crowdfunding undersöcktes av Mollick år 2014. En viktig aspekt i hans studie var hurdana egenskaper i ett projekt som får stödjare att bli attraherade av projektet.

I denna avhandling gräver jag djupare i detta tema. Jag presenterar nya variabler och utför statistiska modeller för att hitta egenskaper i belöningsbaserade crowdfundingprojekt som ökar sannolikheten för att projektet framgångsrikt får den finansiering som det söker. För att se olika aspekter av frågan, använder jag både en logaritmisk regression med projektets framgång som binär beroende variabel och en klassisk linjär regressionsmodell med procentandelen av målet som projektet når som beroende variabel.

9.1.2 Avgränsningar

Eftersom olika crowdfundingnätsidor följer något olika regler har jag avgränsat mina data till projekt som hittas på Kickstarter för att försäkra maximal jämförbarhet projekten emellan.

I avhandlingen undersöks projekt från kategorierna Spel (Games) och Teknologi (Technology), eftersom dessa kategorier anses mest sannolikt erbjuda belönningar med
konkret monetärt värde, och kan därmed anses mest sannolika att attrahera investerare som drivas, i alla fall delvis, av kalkylering och inte enbart altruism.

Projekt vars mål är under 5000 amerikanska dollar eller en motsvarande summa har uteslutits, eftersom projekt med mycket låga målsättningar kan förväntas följa, i alla fall delvis, olika mekanismer än projekt med större mål.

9.2 Bakgrund och teori

9.2.1 Historia och nuläge för crowdfunding


Den första internetbaserade crowdfundingkampanjen utfördes år 1997, och den första internetsidan dedikerad till crowdfunding av olika projekt, ArtistShare, grundades år 2003. Denna sida koncentrerede sig på musikartister, som kunde söka finansiering för sina digitala albumprojekt. (ArtistShare.com)

År 2008 grundades IndieGoGo, och ett år senare Kickstarter, vilka i dagens läge är de två största spelarna på marknaden för belöningsbaserad crowdfunding. Snart efter grundandet av dessa två sidor började crowdfunding explosivt öka i popularitet. Mängden kapital som kanaliserades via crowdfunding mer än förväntades varje år på det tidiga 2010-talet, och förväntas uppgå till 34,4 miljarder dollar år 2015 (exakta siffror är inte ännu tillgängliga). Marknaden förväntas uppgå till 93–96 miljarder dollars år 2025. (Switter 2013; Crowdsourcing.org)

9.2.2 Jämförelse mellan crowdfunding och andra typer av uppstartsfinansiering

I och med att belöningsbaserad crowdfunding är en relativt otradiert typ av finansiering som inte kan räknas vara direkt eget kapital eller skuld på ett traditionellt sätt, är det värt att utföra en kort jämförelse mellan dessa finansieringstyper och belöningsbaserad crowdfunding från ett uppstartsföretags synvinkel.
Traditionell finansiering med eget kapital delas av Robb och Robertson (2012) i tre olika typer: ägarens eget kapital, eget kapital av insiders (dvs. företagarens familj) och utomstående eget kapital. Enligt dem så finansieras en stor majoritet av uppstarts företag åtminstone delvis med hjälp av företagarens eget kapital, vilket är lätt och förklara med att denna typ av kapital inte kräver någon granskning från utomstående och är omedelbart tillgängligt för företagaren. Största negativa sidan i denna form av finansiering är risken, som bärs enbart av företagaren själv. Eget kapital från insiders är betydligt mindre vanligt än ägarens egna kapital, men summor som investeras av familjen, då denna typ av finansiering används, är i genomsnitt lite större än de som investeras av själva företagaren. I fallet av uppstarts företag är också eget kapital från utomstående (affärsängel, riskvilligt kapital, business investerare, statliga investerare och övriga) ovanligt, men då detta kapital erhålls, är summorna typiskt betydligt större än de som i genomsnitt investeras av företagaren själv. Kapital från utomstående kan också medföra sådana fördelar som hjälp i strategisk planering från investerare som vill se framgång för företaget.

Som eget kapital delas även skuld i olika kategorier av Robb och Robertson (2012) på samma sätt som eget kapital. Ägarens skuld innehåller ägarens personliga lån och kreditkort, medan insiderskuld är betydligt mer vanligt än eget kapital från insiders, men ändå används även insiderskuld av relativt få uppstarts företag. Skuld från utomstående är det andra vanligaste sättet av uppstartsfinansiering efter ägarens eget kapital, och används av ungefär en tredjedel av uppstarts företag.

Det finns flera orsaker till varför en företagare kan föredra crowdfunding framför dessa typer av finansiering. Eftersom de flesta av dessa traditionella former av finansiering kräver någon typ av extern granskning av projektet, kan det hända att de inte är lika lätt tillgängliga som belöningsbaserad crowdfunding. Dessutom behöver företagaren inte själv bära hela den monetära risken om hen väljer att använda Kickstarter. Medan en stor majoritet av företagarna faktiskt försöker slutföra projektet och leverera de utlovade belöningarna, finns det inga bestraffningar från Kickstarter sida för företagare som misslyckas i detta. Utöver detta kan tanken på att företagaren inte behöver leverera någon monetär belöning vara attraherande för företagaren.

9.2.3 Aktörerna i crowdfunding

Medlare är gruppen som oftast består av internetbaserade plattformar som erbjuder möjligheten för de två övriga grupperna att hitta varandra och sköter om kommunikation samt överföring av kapital dessa grupper emellan. Regler gällande vilka typer av projekt som godkänns av medlaren, vilken belöning som medlaren får osv. varierar något mellan medlare.


Investerare är individer som understöder crowdfundingprojekt. De undersöker projekt och väljer vilka de vill understöda, och oftast förväntar de sig någon form av belöning som också kan vara immateriell. Utöver det kapital som de vill använda för att understöda projekt samt någon form av dess överföring (t. ex. kreditkort), finns det få begränsningar på vilka som får ta del i ett crowdfundingprojekt som investerare. Vilka projekt som attraherar investerare är denna studies primära frågeställning. (Bouncken, Komorek och Kraus 2015)

9.3 Tidigare forskning

Det finns relativt lite tidigare forskning på crowdfunding i och med att fenomenet är relativt nytt i dess nuvarande form. I detta kapitel presenterar jag några studier på ämnet som publicerats med ett finansiellt perspektiv. Eftersom dessa oftast undersöker flera särdrag av fenomenet crowdfunding, presenterar jag bara de delar som är av omedelbart intresse för min studies syfte.

9.3.1 Belleflamme, Lambert och Schwienbacher 2014

Studien av Belleflamme, Lambert och Schwienbacher är mig veterligen den mest omfattande teoretiska referensramen för mekanismerna av belöningsbaserad crowdfunding.

Författarna ser crowdfunding som ett tvåfasigt spel som de löser till dess perfekta Nash jämvikt. De variabler som de använder i deras matematiska ekvationer är följande:
Tabell 9.1: Variablerna som används av Belleflamme, Lambert och Schwienbacher

<table>
<thead>
<tr>
<th>Variabel</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K$</td>
<td>Mängden kapital som behövs för att starta produktionen</td>
</tr>
<tr>
<td>$s$</td>
<td>Varans baskvalitet (normaliserad till 1)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Marginalnyttan för ökningen av varans kvalitet</td>
</tr>
<tr>
<td>$n_c$</td>
<td>Mängden (massan) stödjare</td>
</tr>
<tr>
<td>$\Pi, \pi_1, \pi_2$</td>
<td>Företagarens totala avkastning ($\Pi$), företagarens avkastning under period 1 ($\pi_1$) och period 2 ($\pi_2$), per definition $\Pi = \pi_1 + \pi_2$</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Gruppnyttan för stödjare</td>
</tr>
<tr>
<td>$p_c, p_r$</td>
<td>Priset för stödjare ($p_c$) och vanliga kunder ($p_r$)</td>
</tr>
</tbody>
</table>

Deras största fynd är relaterade till förhållandet mellan gruppnyttan (vilket definieras som den nytta som stödjare får för deltagandet i projektet, vilket kan innehålla känslan av att höra till en grupp), mängden kapital som behövs för att starta produktionen och företagarens totala avkastning. Deras resultat kan summeras enligt följande:

$$
\Pi_p = \begin{cases} 
\frac{1}{16} \left(1 + \frac{8}{1 + 2\sigma (R - K)}\right)^2, & \bar{K} \leq K \\
\frac{1}{4} \left(1 + \frac{\sigma^2}{1 + 4\sigma} - K\right), & K \leq \bar{K} \\
0, & \bar{R} < K 
\end{cases}
$$

(1)

$\bar{K}$ står för kapitalet som samlas innan produktens offentliga lansering och $\bar{K}$ är den maximala mängden startkapital som kan samlas med hjälp av crowdfunding.

Ett annat intressant fynd i studien är att om företagaren kan prisdiskriminera mellan stödjare i en crowdfundingkampanj och vanliga kunder, betalar stödjare alltid mera för produkten.

**9.3.2 Mollick (2014)**

I sin studie från 2014 är Ethan Mollicks målsättning att svara på grundläggande frågor kring crowdfunding. Han studerar vilka faktorer som påverkar framgången för en crowdfundingkampanj samt crowdfundingsegeografi. Eftersom den senare aspekten är av lite intresse ur min studies synpunkt, koncentrerar jag mig på att presentera den första.
Mollick använder flera logistiska regressionsmodeller för att undersöka vilka faktorer som gör en crowdfundingkampanj framgångsrik. Studien använder Kickstarter som datakälla. Hans beroende variabel är naturligtvis projektets framgång, och de oberoende variablerna (i den första delen) är de följande: projektets mål (Log(goal)), dess längd i dagar (Duration), huruvida projektet är ”Featured” (visas mer synligt på Kickstarter) (Featured), om projektsidan på Kickstarter innehåller en video (Video), om projektet uppdateras inom de tre första dagarna av kampanjen (Quick update), om det finns stavfel i projektets beskrivningstext (Spelling error) och mängden Facebook vänner som projektskaparen har (Log(FBF)). Den sista variabeln är även uppdelad i kvartal för vissa modeller. Mollicks resultat är följande:

Tabell 9.2: Mollicks resultat

<table>
<thead>
<tr>
<th>Variabel</th>
<th>Modell 1</th>
<th>Modell 2</th>
<th>Modell 3</th>
<th>Modell 4</th>
<th>Modell 5</th>
<th>Modell 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(goal)</td>
<td>0.23***</td>
<td>0.22***</td>
<td>0.19***</td>
<td>0.23***</td>
<td>0.18***</td>
<td>0.19***</td>
</tr>
<tr>
<td>Duration</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
</tr>
<tr>
<td>Featured</td>
<td>20.47***</td>
<td>22.13***</td>
<td>17.90***</td>
<td>20.45***</td>
<td>19.77***</td>
<td>17.14***</td>
</tr>
<tr>
<td>Video</td>
<td>4.30***</td>
<td>4.27***</td>
<td>4.26***</td>
<td>4.30***</td>
<td>4.27***</td>
<td>4.26***</td>
</tr>
<tr>
<td>Quick update</td>
<td>2.73***</td>
<td>2.69***</td>
<td>2.70***</td>
<td>2.73***</td>
<td>2.69***</td>
<td>2.70***</td>
</tr>
<tr>
<td>Spelling error</td>
<td></td>
<td></td>
<td></td>
<td>0.36***</td>
<td>0.33***</td>
<td>0.38***</td>
</tr>
<tr>
<td>Log(FBF)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.83***</td>
<td>2.77**</td>
</tr>
<tr>
<td>FBF lower 25 %</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.52***</td>
</tr>
<tr>
<td>FBF 25%-50%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.01</td>
</tr>
<tr>
<td>FBF 50%-75%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.46***</td>
</tr>
<tr>
<td>FBF top 25%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.64***</td>
</tr>
<tr>
<td>Kategorikontroll</td>
<td>Ja</td>
<td>Ja</td>
<td>Ja</td>
<td>Ja</td>
<td>Ja</td>
<td>Ja</td>
</tr>
<tr>
<td>Konstant</td>
<td>213.59***</td>
<td>19.34***</td>
<td>124.12***</td>
<td>296.63***</td>
<td>9.04***</td>
<td>127.01***</td>
</tr>
<tr>
<td>Observationer</td>
<td>22,651</td>
<td>9,603</td>
<td>22,651</td>
<td>22,651</td>
<td>9,603</td>
<td>22,651</td>
</tr>
<tr>
<td>Chi^2</td>
<td>3021.57</td>
<td>1621.44</td>
<td>4578.38</td>
<td>3059.98</td>
<td>2269.24</td>
<td>4935.20</td>
</tr>
<tr>
<td>p</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.10</td>
<td>0.13</td>
<td>0.15</td>
<td>0.10</td>
<td>0.18</td>
<td>0.16</td>
</tr>
</tbody>
</table>

***p<0.01, **p<0.05, *p<0.1

Som man kan se i tabellen, är nästan alla variabler som undersöks statistiskt mycket signifikanta åt ett eller annat håll, och har därmed en effekt på projektets framgång. Det är värt att märka att i Mollicks metod betyder koefficienten på under 1 att effekten är negativ. Det är också värt att märka att pseudo R²-värden är relativt låga (det specificeras inte av Mollick vilken pseudo R² som han använder), vilket innebär att många variabler saknas från modellerna.
9.3.3 **Colombo, Franzoni & Rossi-Lamastra (2015)**

Såsom Mollick (2014) undersöker Colombo, Franzoni och Rossi-Lamastra vilka faktorer som påverkar framgången av en crowdfundingkampanj. Deras betoning är dock på sociala nätverk och typer av belöning som stödjare får. De bygger två hypoteser (av vilka den första har två delar) om den s.k. interna sociala kapitalets, dvs. effekten av projektgrundarens sociala kapital inom crowdfunding-nätverket, på kampanjens framgång:

1. Projektgrundarens intern social kapital har en positiv effekt på a) mängden tidiga stödjare som kampanjen får och b) mängden tidigt kapital som kampanjen får.

2. Dessa två faktorer förklarar den nytta som projektgrundaren får för sin intern social kapital.

Deras variabler utöver tidigt kapital (Early_Capital) och stödjare (Ln_Early_Backers) är antalet LinkedIn-kontakter som projektgrundaren har (External_LinkedIn), grundarens kön (D_Individual_Male, D_Individual_Female), kampanjens längd (Duration), om belöningens typ är s.k. ego-höjande (D_Ego_Boosting), medför känslan av tillhörighet (D_Community_Belonging) eller skräddarsydd (D_Customized), hur många visuella drag som projektsidan har (Ln_Visuals), mängden länkar till websidor med mera information om projektet (More_Information), om projektet grundades i USA (D_USA) och projektets målkapital (Ln_Target_Capital). Deras resultat summeras i tabell 9.3.

**Tabell 9.3: Colombos, Franzonis och Rossi-Lamastras resultat**

<table>
<thead>
<tr>
<th></th>
<th>Modell I</th>
<th>Modell II</th>
<th>Modell III</th>
<th>Modell IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal_Social_Capital</td>
<td>0.52**</td>
<td>0.662***</td>
<td>0.235***</td>
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Som man kan se i tabellen, så håller båda av författarnas hypoteser: det interna sociala kapitalet har en positiv effekt på projektets framgång, men denna effekt försvinner då man tar med tidiga stödjare och tidigt kapital i modellen.

### 9.4 Metod

I och med att mitt främsta mål är att hitta de faktorer som påverkar ett crowdfundingprojekts framgång, har jag framgången som binär beroende variabel. Därmed använder jag en logistisk regression (logit). (Cox 1958) För att titta på problemet från en lite annan synvinkel, utför jag också en klassisk linjär regressionsmodell (CLRM), med procentandelen av målet som projektet har nått som beroende variabel.

Min Logit-modell, som följer efter den vanliga logit-formuleringen (Brooks 2008), är den följande:

\[
P_i = \frac{1}{1 + e^{-(\beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \beta_7 x_{7i} + \beta_8 x_{8i} + \beta_9 x_{9i} + \beta_{10} x_{10i} + \beta_{11} x_{11i} + \beta_{12} x_{12i} + u_i)}}
\]  
(2)

Min CLRM tar den följande formen:

\[
y_i = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \beta_7 x_{7i} + \beta_8 x_{8i} + \beta_9 x_{9i} + \beta_{10} x_{10i} + \beta_{11} x_{11i} + \beta_{12} x_{12i} + u_i
\]  
(3)

Mina oberoende variabler är de följande:

- \(x_{2i} = \ln(\text{Goal})\), projektets kapitalmål
- \(x_{3i} = \ln(\text{Duration})\), kampanjens längd
- \(x_{4i} = \text{Staff pick}\), huruvida projektet har blivit utvalt av Kickstarters personal som projekt som de personligen tycker om. Dessa projekt får extra synlighet på Kickstarter.
- \(x_{5i} = \text{Video}\), huruvida kampanjsidan har en video
- \(x_{6i} = \text{Quick update}\), huruvida projektsidan uppdateras inom de tre första dagarna
- \(x_{6i} = \ln(\text{FBF})\), mängden Facebook vänner som projektgrundaren har, ifall det finns ett Facebook-konto kopplat till projektet
$x_{7i} = Publicity$, huruvida projektet har fått synlighet i medierna

$x_{8i} = Reward\ value$, genomsnittliga nivån av värdet på belöningar för projektets stödjare i förhållande till kontributionen som behövs för att erhålla belöningen. Ett projekt kan ha, och i de flesta fall har, flera olika nivåer. En individ belöning definieras som 0 om belöningen inte har ett monetärt värde, 1 om värdet är under 75 % av kontributionen, 2 om värdet är mellan 75 % och 125 % av kontributionen och 3 om värdet är 125 % av kontributionen eller mera. Det utförs även en känslighetsanalys var dessa gränsvärden förändras.

$x_{9i} = Average\ time\ to\ delivery$, tiden från projektets slutdatum till belöningens leverans

$x_{10i} = Number\ of\ reward\ levels$, mängden belöningsnivåer

$x_{11i} = Average\ reward\ value\ for\ chosen\ rewards$, samma som ”reward\ value” ovan, men räknad som ett medeltal av alla nivåer med åtminstone en stödjare, och vägd med antalet stödjare för varje nivå

$x_{12i} = Average\ delivery\ time\ for\ chosen\ rewards$, samma som ”time\ to\ delivery” ovan, men med likadana förändringar som ”average\ reward\ value\ for\ chosen\ rewards” ovan

Modelldiagnostik kördes där det behövdes, och heteroskedasticitet och multikollinearitet löstes med hjälp av ekonometriprogrammet Gretls automatiska heteroskedasticitetskorrigerande samt utelämnandet av en variabel från multikollinearitätsvariabelpar.

### 9.5 Data

Data för studien har samlats från Kickstarter, den största webbsidan för belöningsbaserad crowdfunding för projekt. De flesta data som behövs för studien finns tillgängliga på sidan. Synlighet i medierna och värdet på belöningar har undersökt med hjälp av sökmotorn Google.

Eftersom Kickstarter inte erbjuder något sätt att gå igenom projekt vars kampanj har tagit slut som en lista (projektsidan blir dock kvar; man måste bara känna till dess URL), förblev det mest behövligt att välja nuvarande projekt som data. Projekt ordnades i en lista enligt deras slutdatum. Datainsamlingsprocessen var tvåfasig: i den första fasen samlades största mängden av data för projektet och efter att projektet hade tagit slut samlades den slutliga summan som projektet lyckades samla och slutliga mängden stödjare totalt och per belöningsnivå.
Nedre gränsen på projektets mål sattes på 5000 dollar, utan övre gräns. Mollick (2014) hade övre gränsen på 1 000 000 dollar, men sådana projekt är mycket ovanliga, och inga sådana finns i mina data trots att jag inte uteslöt dessa från början.

9.6 Resultat

9.6.1 Logit och CLRM-modeller

De flesta oberoende variabler som undersöktes visade sig vara signifikanta åtminstone i vissa modeller. Variablerna Video, Delivery time och Chosen delivery time (samt en dummyvariabel för huruvida projektet hade Facebook kopplat till sig) visade sig dock i ingen av modellerna att ha statistisk signifikans, och dessa togs därmed bort från de slutliga modellerna.

Alla modeller i en tabell lyder enligt samma logik: beroende variabeln är den samma och tabellen visar koefficienterna för varje variabel som inkluderades i modellen i fråga. Ett tomt fält betyder att variabeln inte inkluderades i tabellen i fråga.

(Pseudo) R²-värden i mina modeller är generellt ungefär 0,5 i logit-modeller och lite över 0,3 i CLRM-modeller, vilket innebär logit-modellerna passar till data någorlunda bättre än CLRM-modellerna. Därmed kan man konstatera att det finns ännu en hel del faktorer som förklarar fenomenet och som inte tagits i beaktande i denna studie, men överlag passar särskilt mina logit-modeller till data betydligt bättre än till exempel Mollicks (2014) som hade pseudo R²-värden runt 0,15. Det är dock värt att märka att Mollick aldrig specificerade vilken pseudo R²-statistik som han använde, så det är möjligt att dessa resultat inte är direkt jämförbara.

Jag har även utfört en känslighetsanalys i vilken jag har förändrat de subjektiva gränsvärdena för belöningsnivåer för att se huruvida ändringen på dessa värden har inverkan på signifikansnivåer av Reward value-variabeln. Mina resultat visar att medan små förändringar i signifikans sker, är resultaten i stora drag likadana även om man ändrar värdena till 50%/150 %, 60%/ 140 % eller 90 %/ 110 %.
Tabell 9.4: Resultat från logit-modeller

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<th>Konstant</th>
<th>Ln(Goal)</th>
<th>Ln(duration)</th>
<th>Staff pick update</th>
<th>Publicity</th>
<th>Ln(FBF)</th>
<th>Reward value</th>
<th>Ln(No. of reward levels)</th>
<th>Chosen reward value</th>
<th>McFaddens pseudo R²</th>
<th>Procentandel rätta förutsägelse</th>
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Beroende variabel: Framgång (binär variabel)

*p<0.1 **p<0.05 ***p<0.01
Tabell 9.5: Resultat från CLRM-modeller

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<td>0.38</td>
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</tbody>
</table>

Beroende variabel: Procentandel av målet som projektet nått

*p< 0.1 **p<0.05 ***p<0.01
Utöver de föregående modellerna har även de variabler som är applicerbara till alla projekt regresserats mot varandra för att få vidare insikter i dynamiken. De variabler som var binära har regresserats med hjälp av logit-modeller, medan de icke-binära variablerna har undersökt med hjälp av CLRM-modeller. Resultaten från dessa modeller presenteras i tabellen nedan. Som tidigare så har modelldiagnostik körts och applicerats vid behov.

Tabell 9.6: Interaktioner variabler emellan

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<th></th>
<th>Constant</th>
<th>Ln(Goal)</th>
<th>Ln(Duration)</th>
<th>Staff pick</th>
<th>Quick update</th>
<th>Publicity</th>
<th>Reward value</th>
<th>Ln(No. of reward levels)</th>
<th>(Pseudo) R²</th>
<th>Modell</th>
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<td>1.19**</td>
<td>1.50***</td>
<td>0.59**</td>
<td>0.85**</td>
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<td>-0.90</td>
<td>-0.02</td>
<td>-0.78*</td>
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<td>0.31***</td>
<td>0.08</td>
<td>CLRM</td>
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*p < 0.1 **p < 0.05 ***p < 0.01

9.7 Diskussion och konklusion

En av de största frågorna som denna avhandling har försökt hitta svar på är huruvida stödjare är huvudsakligen drivna av kalkylering av personlig nytta. I och med att det genomsnittliga värdet på valda belöningar är 1.24 (där 2 betyder belöning som ungefär motsvarar ”investeringen” utan diskontering), kan man lätt konstatera att detta inte är fallet. Det är dock värt att märka att i de flesta modellerna har den genomsnittliga belöningsnivån dock en statistiskt signifikant och positiv inverkan på projektets chanser till framgång, vilket tyder på att trots att belöningen inte är den huvudsakliga motivatorn, är den dock en motivator bland andra. Dessutom är det värt att komma ihåg att stödjarmassan i Kickstarter består av miljoner av individer med sina egna värderingar och motivationer att delta i projektet. Det är dock värt att nämnna att tiden till leverans inte hade signifikans i någon modell, vilket innebär att stödjare inte är särskilt sofistikerade när det gäller diskontering och pengarnas tidsvärde.

Så som i tidigare studier hittar även jag bevis på att mått på kvalitet på projekt och beredskap av projekts grundare spelar en viktig roll i förklaringen av projektets framgång. Trots att det inte finns några entydiga kriterier som får ett projekt att väljas som ”Staff Pick”, är det klart att detta är det främsta teckenet på projekt som visar hög kvalitet. Eftersom

Projektets publicitet hade en positiv inverkan på projekts framgång, vilket är knappast överraskande. I och med att jag också har räknat publicitet som kommit under kampanjtiden, är det svårt att nämna kausalitetens håll: projekt som har nått framgång redan tidigt i kampanjen lockar mer sannolikt uppmärksamhet från media. Däremot kan denna uppmärksamhet medföra vidare stödjare, vilka inte skulle fångas av modellen om man bara räknade publicitet som kommit före kampanjen. Medan ingen modell hittade bevis på att kopplingen av en Facebook-profil till kampanjen hade signifikant inverkan på framgång, är det svårt att märka att om en profil var kopplad, hade mängden vänner en signifikant inverkan på framgången. Därmed kan jag konstatera att det verkar finnas en koppling mellan grundarens sociala nätverk och projektets chanser för framgång.

Projektets mål hade en signifikant negativ inverkan på framgången i nästan varje modell, vilket är lätt att förklara: det är lättare att träffa ett lägt mål. Som ett intressant fynd hade projektlängden också en negativ inverkan på framgång, men detta var bara signifikant i några få fall. Detta hittades även av Mollick år 2014, som antog att detta sannolikt beror på brist på självförtroende från grundarens sida.

Inga stora skillnader mellan spel- och teknologiprojekt hittades; de största var inverkan av belöningars värde och publicitet, vilka var signifikanta för spelprojekt men inte teknologiprojekt. Belöningarnas inverkan beror sannolikt på att spelprojekt är mer homogena, vilket kan leda till att det är lättare för stödjare att uppskatta värdet på belöningar, och kalkylera mer exakt. Publicitetens effekt kan sannolikt förklaras med den
stora mängden media på internet som fokuserar på spel: det är lättare för ett lovande spelprojekt att få synlighet genom dessa medier.

Applicerbara delar av tidigare studier verkar har kommit till likadana slutsatser som jag gällande effekten av projektmålet, tecken på beredskap, projektets längd osv. på projektets framgångschanser. Det är dock värt att märka att min studie, som innehåller mått på publicitet, mängden belöningssnivåer och den generella belöningssnivån, visar någorlunda högre (Pseudo) $R^2$-värden, vilket indikerar att mina modeller passar data någorlunda bättre än de tidigare studierna.

Överlag kan jag konstatera att trots att jag har hjälpt till med att täppa några luckor i kunskapen om crowdfunding, finns det en hel del forskning som ännu måste göras – crowdfunding blir större och viktigare varje dag.
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Other sources

APPENDIX 1: CORRELATION MATRIX OF VARIABLES

<table>
<thead>
<tr>
<th></th>
<th>Success</th>
<th>Ln(goal)</th>
<th>Staff pick</th>
<th>Video</th>
<th>Quick update</th>
<th>FBF Dummy</th>
<th>Publicity</th>
<th>Comments</th>
<th>Ln(duration)</th>
<th>Ln(No. Of reward levels)</th>
<th>Average reward value</th>
<th>Chosen reward value</th>
<th>Average time to delivery</th>
<th>Chosen delivery time</th>
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<td>Success</td>
<td>1,000</td>
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<td>Ln(goal)</td>
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<td>Video</td>
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<td>0.197</td>
<td>1,000</td>
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<td>Quick update</td>
<td>0.470</td>
<td>0.116</td>
<td>0.261</td>
<td>0.132</td>
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<td>FBF Dummy</td>
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<td>-0.089</td>
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<td>0.027</td>
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<td>Ln(duration)</td>
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<td>Ln(No. Of reward levels)</td>
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<td>0.284</td>
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<td>Chosen delivery time</td>
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## APPENDIX 2: FULL COEFFICIENTS TABLE OF LOGIT TEST WITH 50%/150% REWARD VALUE LEVEL CUTOFFS

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<th></th>
<th>Constant</th>
<th>Ln(Goal)</th>
<th>Ln(duration)</th>
<th>Staff pick</th>
<th>Quick update</th>
<th>Ln(FBF)</th>
<th>Publicity</th>
<th>Reward value 50%</th>
<th>Ln(No. of reward levels)</th>
<th>Chosen reward value 50%</th>
<th>McFadden’s pseudo R²</th>
<th>Percentage of correct predictions</th>
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<td><strong>All projects</strong></td>
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<td>Model 1</td>
<td>4.52</td>
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<td>-0.45</td>
<td>2.38***</td>
<td>2.07***</td>
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<td>1.29***</td>
<td>0.47</td>
<td>88.7</td>
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<td>1.27***</td>
<td>0.47</td>
<td>88</td>
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<td><strong>Projects with backers</strong></td>
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<tr>
<td>Model 3</td>
<td>6.56*</td>
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<td>-0.57</td>
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<td>0.96**</td>
<td>0.64**</td>
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<td>1.57***</td>
<td>0.95**</td>
<td>0.64***</td>
<td>0.40</td>
<td>84.9</td>
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<td>Model 5</td>
<td>10.84**</td>
<td>-1.41***</td>
<td>-1.56</td>
<td>1.74**</td>
<td>2.52***</td>
<td>2.30*</td>
<td>1.65***</td>
<td>1.52***</td>
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<td>Model 6</td>
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<td>1.77**</td>
<td>2.74***</td>
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<td>1.63***</td>
<td>1.48***</td>
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<td><strong>Technology projects</strong></td>
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<td>Model 7</td>
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<td>Model 8</td>
<td>-1.43</td>
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<td>3.76***</td>
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<td>Model 9</td>
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<td>0.57</td>
<td>92.2</td>
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</table>

Dependent variable: Success (binary variable)

* = [0.1 ≥ p > 0.05]; ** = [0.05 ≥ p > 0.01]; *** = [0.01 ≥ p]
APPENDIX 3: A DETAILED DESCRIPTION OF THE FRAMEWORK BY BELLEFLAMME, LAMBERT AND SCHWIENBACHER (2014)

This section offers a more detailed description of the framework created by Belleflamme, Lambert and Schwienbacher, presented in 2.1.

*Period 2*

The authors start by solving the second period of the game, that is, the period after the launching of the product for regular customers.

They recognize that there exists a limit at which consumers are indifferent between pre-ordering and not. This limit is identified by the taste parameter $\theta_c = 1 - n_c$. Since consumers whose taste parameter $\theta > 1 - n_c$ already ordered at period one, the potential customers during period two are such that their taste parameter $\theta$ follows the following rule: $\theta_c \geq \theta \geq 0$.

They will buy the product if the second period price $p_r$ follows $\theta - p_r \geq 0$, or $\theta \geq p_r$. A taste parameter that follows this rule is defined as $\theta_r$. As the authors assume zero marginal costs of production for the sake of simplicity (in many popularly crowdfunded products, such as digitally distributed computer games, the assumption of zero or negligible marginal costs of production may well even be a realistic one), the entrepreneur’s period two profit is defined as $\pi_2 = p_r(\theta_c - p_r)$.

The entrepreneur is thus faced with the following maximization program at period two:

$$\max_{p_r} p_r (\theta_c - p_r).$$

Extrapolating this into $p_r \theta_c - p_r^2$ and taking the first order derivative with regard to $p_r$, we find that $\pi_2$ is maximized when $p_r = \frac{\theta_c}{2}$. The amount of profit under this optimum is thus found with the equation $\pi_2 = \frac{\theta_c^2}{4}$, which simplifies to $\pi_2 = \frac{\theta^2}{4}$. 
**Period 1**

Having solved period two, the authors then move on to solve period one. The taste parameter $\theta_c$, used to identify the indifferent consumer between pre-ordering and not, can be identified in the context of period one by rewriting the equation $\theta_c (1 + \sigma) - p_c = \theta_c - p_r$ into $\theta_c = \frac{p_c - p_r}{\sigma}$. (Recall here that $\sigma$ denotes the community benefits from crowdfunding and $p_c$ denotes the price of the product paid by crowdfunders.) As we previously solved $p_r$ and found it to equal $\frac{\theta_c}{2}$, we can further rewrite the equation as $\theta_c = \frac{1}{\sigma} (p_c - \frac{\theta_c}{2})$. Simplifying this, we have $\theta_c = \frac{2p_c}{1+2\sigma}$. Since the fraction of crowdfunders from the mass of total consumers is $1 - \theta_c = 1 - \frac{2p_c}{1+2\sigma}$, which leads to a total profit of $\pi_1 = p_c \left(1 - \frac{2p_c}{1+2\sigma}\right)$ in period 1, and we found the second period profit $\pi_2$ to equal $\frac{\theta^2}{4}$ under optimal pricing at period two, the optimization of total profit by the entrepreneur, to be maximized at period one, becomes the following:

$$\max_{p_c} p_c \left(1 - \frac{2p_c}{1+2\sigma}\right) + \frac{1}{4} \left(\frac{2p_c}{1+2\sigma}\right)^2,$$

where the following constraints apply

$$p_c \left(1 - \frac{2p_c}{1+2\sigma}\right) \geq K \quad \text{(since the period one profit $\pi_1$ must be at least equal to $K$)}$$

and

$$0 \leq \frac{2p_c}{1+2\sigma} \leq 1 \quad \text{(since the mass $n$ of all potential consumers is by definition 1).}$$

Maximizing this function, we get the (unconstrained) optimum

$$p_c^* = \frac{(1+2\sigma)^2}{2(1+4\sigma)}.$$

We find the values of $\pi_1$ that satisfy the first constraint by placing the acquired value of $p_c^*$ into the first constraint equation. Simplifying the equation we get by doing so, we get

$$K \leq \frac{\sigma(1+2\sigma)^2}{(1+4\sigma)^2}.$$

This is the upper limit of the capital requirement that allows for optimal pricing, which we define as $K^*$. 
To find the taste parameter for the indifferent consumer under optimum, we place $p_c^*$ to the equation $\theta_c^* = \frac{2p_c}{1+2\sigma}$. To see if the second constraint is satisfied, we simplify this equation and examine it in light of the second constraint:

$$0 \leq \frac{1+2\sigma}{1+4\sigma} \leq 1.$$ 

This is clearly true for all values of $\sigma$. The second constraint is thereby satisfied.

**The unconstrained case**

As we previously established, the values $p_c^*$ and $\theta_c^*$ denote the price for crowdfunders and the taste parameter at which the consumer is indifferent between pre-ordering and not, respectively, under optimum. If $K \leq \bar{K}$, we can use these values to solve the total profit at unconstrained optimum, which is

$$\Pi^* = \pi_1^* + \pi_2^* - K = \frac{\sigma(1+2\sigma)^2}{(1+4\sigma)^2} + \frac{1}{4} \left(\frac{1+2\sigma}{1+4\sigma}\right)^2 - K = \frac{(1+2\sigma)^2}{4(1+4\sigma)} - K.$$ 

After establishing the unconstrained optimum, the authors move on to compare it to two benchmarks, which help to shed light on the dynamics of pre-ordering.

**The first such benchmark** is the price in the case where the entrepreneur is not able to price discriminate between consumers. In this case, instead of maximizing the profit by taking into account both periods, she would maximize her profit by maximizing the uniform price $p_u$. As the indifferent consumer in this case is identified by the equation $\theta - p_u = 0$, the entrepreneur’s profit maximization program becomes

$$\max_{p_u} p_u (1 - p_u).$$ 

It is easy to see that the profit is here maximized at $p_u = \frac{1}{2}$, and all consumers who buy the product have a taste parameter of $\theta \geq \frac{1}{2}$. Profit at this price is $\frac{1}{4}$. Comparing this to the optimal prices (when discrimination is possible) for regular consumers, which can be expressed as $p_r^* = \frac{1}{2} - \frac{\sigma}{1+4\sigma}$, and crowdfunders, which can be expressed as $p_c^* = \frac{1}{2} + \frac{\sigma^2}{1+4\sigma}$, we find that

$$p_r^* = \frac{1}{2} - \frac{\sigma}{1+4\sigma} < p_u = \frac{1}{2} < p_c^* = \frac{1}{2} + \frac{\sigma^2}{1+4\sigma}.$$
This means that regular consumers pay less in the presence of price discrimination than without it, while crowdfundingers pay more. This also means that if there is price discrimination, crowdfundingers always pay more than regular consumers, assuming nonzero community benefits. This is one of the central findings which I have examined in light of my results.

It is also worth noticing that the presence of price discrimination increases the profit of the entrepreneur. This is due to an increasing market: in the absence of price discrimination, the indifferent consumer is found at $\theta = \frac{1}{2}$, while in the presence thereof, she is found at $\theta^*_r = \frac{1}{2} - \frac{\sigma}{1+4\sigma} < \frac{1}{2}$ (since $\theta^*_r - p^*_r \geq 0 \Rightarrow \theta^*_r \geq p^*_r$, and $p^*_r = \frac{1}{2} - \frac{\sigma}{1+4\sigma}$), since the optimal profit in the presence of price discrimination can be expressed as

$$\Pi^* = \frac{(1+2\sigma)^2}{4(1+4\sigma)} - K = \frac{1}{4} + \frac{\sigma^2}{1+4\sigma} - K,$$

and

$$\frac{1}{4} + \frac{\sigma^2}{1+4\sigma} - K > \frac{1}{4} - K.$$  
(Recall that profit in the absence of price discrimination is $\frac{1}{4}$.)

The second benchmark is the situation in which the entrepreneur can commit to the second period price during period one. Since the indifferent consumer in period one is given by $\theta^*_c = \frac{p_c-p_r}{\sigma}$, which, in turn, equals $1 - n_c$, so $n_c = 1 - \frac{p_c-p_r}{\sigma}$, the entrepreneur’s profit is maximized with the function

$$\max_{p_c,p_r} p_c \left( 1 - \frac{p_c-p_r}{\sigma} \right) + p_r \left( \frac{p_c-p_r}{\sigma} - p_r \right),$$
which is subject to $1 \geq \frac{p_c-p_r}{\sigma} \geq p_r \geq 0$.

Taking partial derivatives of the function with regard to $p_c$ and $p_r$, and solving these as a pair of simultaneous equations, we find that $p_c = \frac{1+\sigma}{2}$ and $p_r = \frac{1}{2}$. This also leads to $\frac{p_c-p_r}{\sigma} = p_r$, making the part $\frac{p_c-p_r}{\sigma} - p_r$ of the function, denoting the mass of buyers at period two, universally zero. From this, we see that no consumers are willing to buy the product at period two, so the entrepreneur optimally chooses to forgo opening the market at all during period two. All consumers are thus crowdfundingers, who are willing to pay the price $\theta (1 + \sigma)$ for the product. The profit in this case is $p_c \left( 1 - \frac{p_c-p_r}{\sigma} \right) - K = \frac{1+\sigma}{4}$. It is easy to show that the inequality $\frac{(1+2\sigma)^2}{4(1+4\sigma)} - K < \frac{1+\sigma}{4} - K$ holds, and thus the profit is greater than $\Pi^*$. Therefore, the entrepreneur suffers from not being able to set the future price in advance.
**The constrained case**

In the unconstrained case, the entrepreneur is able to set the price in accordance with what is optimal to them. However, if the capital raised during period one at optimal conditions, $\bar{K}$, is smaller than the required amount of capital to start production, $K$, the entrepreneur must adjust the first-period price to this. The first-period price in this case is found with the equation

$$p_c \left(1 - \frac{p_c - p_r}{\sigma}\right) = \bar{K},$$

which leads to $2p_c^2 - (1 + 2\sigma)p_c + (1 + 2\sigma)K = 0$.

As per the formula for second-degree polynomials, this polynomial only has real roots if

$$\left[(1 + 2\sigma)p_c\right]^2 - 4 \times 2p_c^2 (1 + 2\sigma)K \geq 0,$$

and thereby if $K \leq \frac{1 + 2\sigma}{8}$. This value is defined as $\bar{K}$. This also tells us that if the initial capital requirement exceeds a certain threshold, financing the project via crowdfunding is no longer a viable option.

The maximum and minimum values of $p_c$ in the aforementioned polynomial are $p_c = \frac{1 + 2\sigma}{2}$ and $p_c = 0$, respectively, both achieved when $K = 0$. (This also ensures that $0 < \theta_c < 1$.) As such, the roots of the polynomial are $0 < p_c^- < p_c^+ < 1$. As the second period profit increases as a $p_c$ increases, the entrepreneur will prefer $p_c^+$ over $p_c^-$. Therefore, the entrepreneur will set $p_c$ to

$$p_c = \frac{(1 + 2\sigma)^2 + \sqrt{(1 + 2\sigma)^2 - 4 \times 2p_c^2 (1 + 2\sigma)K}}{2 \times 2},$$

which is $\frac{1}{4} [1 + 2\sigma + \sqrt{(1 + 2\sigma)(1 + 2\sigma + 8\bar{K})}]$.

Since the first-period profit in this case always equals $\bar{K}$, the total profit of the entrepreneur is equal to the second-period profit. Thus

$$\bar{\Pi} = \bar{\pi}_2 = \frac{\theta_c^2}{4} = \frac{1}{4} \left(\frac{2p_c^+}{1 + 2\sigma}\right)^2 = \left(\frac{p_c^+}{1 + 2\sigma}\right)^2 = \frac{1}{16} \left(\frac{1 + 2\sigma + \sqrt{(1 + 2\sigma)(1 + 2\sigma + 8\bar{K})}}{1 + 2\sigma}\right)^2 = \frac{1}{16} \left(1 + \sqrt{\frac{8\bar{K}}{1 + 2\sigma}}\right)^2.$$

Having reached this conclusion, we can now summarize the result as a lemma that dictates the profit gained through a project financed with crowdfunding of the pre-ordering type under different capital requirements:
\[
\Pi_p = \begin{cases} 
\frac{1}{4} + \frac{\sigma^2}{1 + 4\sigma} - K, & K \leq \bar{K} \\
\frac{1}{16} \left(1 + \sqrt{\frac{8}{1 + 2\sigma(\bar{K} - K)}}\right)^2, & \bar{K} \leq K \leq \tilde{K} \\
0, & \tilde{K} < K
\end{cases}
\]

\[
\bar{K} = \frac{\sigma(1 + 2\sigma)^2}{(1 + 4\sigma)^2}, \quad \tilde{K} = \frac{1 + 2\sigma}{8}
\]

From this set of equations, we can see that the profit gained through crowdfunding, according to the authors, decreases as \( K \) increases, and that it increases as the magnitude of community benefits \( \sigma \) increases.