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Crowdfunding: Determinants of success and funding dynamics

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Abstract

Over the past years crowdfunding emerged as an alternative funding channel for entrepreneurs. In contrast to traditional financiers (banks, venture capital firms or angel investors), crowdfunding allows individuals to fund entrepreneurs directly even with small amounts. We received individual-level data from Startnext, the biggest crowdfunding platform in Germany, enabling us to investigate funding dynamics, explore pledgers' motivations and analyze projects' success determinants. We find substantial heterogeneity of how success (about half of the 2,252 projects in our dataset get funded) is reached. When two thirds of the funding duration has passed, the majority of projects (59%) that eventually get funded are not on a successful track. However, pledges in the final phase can only partially be explained by a rush to get still unfunded projects succeed. Overall, 18.7% of pledges are made to projects that already reached their funding target and our analysis shows that the increased funding towards the deadline is due to pledges to projects that already made it, particularly pre-selling pledges.

JEL classifications: D03, G32

Keywords: crowdfunding, entrepreneurial finance, donations, pre-selling

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1 Introduction

One of the biggest challenges an entrepreneur faces is to get funding for the project. Traditionally, financial intermediaries, such as banks, venture capital firms or angel investors, serve to finance entrepreneurial endeavors. In the recent years, an alternative funding channel for entrepreneurs – crowdfunding – emerged. In contrast to traditional financiers, crowdfunding allows individuals to fund entrepreneurs directly even with small amounts. Specifically, the crowd (the mass of individuals) provides financial resources to the entrepreneur in return for equity stakes, interest payment, the future product/service, or a non-monetary reward. The connection between the crowd and the entrepreneurs is often facilitated by an online platform. Entrepreneurs present their projects on the platform and users are able to inform themselves about the projects. Hence, users take individual decisions to invest/lend/purchase/donate, but fund as a crowd. Crowdfunding experienced exponential growth in the last couple of years and by now has reached a substantial funding volume.¹ Given this success, crowdfunding appears to have tapped a new funding channel for entrepreneurs. It can be categorized into crowd pre-selling, crowd donations, crowd equity and crowd lending (see Hemer, 2011; Belleflamme et al., 2014). Crowd pre-selling and crowd donations introduce innovative interactions to the entrepreneurial finance context (in contrast to lending and equity, essentially crowd analogies of traditional financing instruments) and they account for almost half of the crowdfunding volume raised in 2012 (massolution, 2013). While some crowdfunding sites focus only on crowd donations, several very successful platforms offer crowd pre-selling and also allow donations to be made to projects. The most prominent example of this type is Kickstarter (www.kickstarter.com). At such platforms, crowdfunding entrepreneurs commonly set a funding target for their project which serves as a threshold. The project gets funded only if the target is reached within a specified amount of time. That is, individuals pledge to support the project and their pledges turn into payments in case the project succeeds in reaching its funding target.

A sound understanding of the behavioral mechanisms at donations/pre-selling platforms seems essential, but so far only few empirical studies using data from such sites exist (see Moritz and Block, 2013, for a recent literature survey). Mollick (2014) explores project-level data from Kickstarter, Giudici et al. (2013) gather project-level data from 11 Italian platforms and Kuppuswamy and Bayus (2013) collect the number of backers of Kickstarter projects over time. To the best of our knowledge so far no study investigated single transactions data from a donations/pre-selling crowdfunding platform. Such individual-level data should provide further insights into the dynamics of crowd transactions and motivations of pledgers. Startnext, the biggest crowdfunding platform in Germany, provided us with all

¹According to the Crowdfunding Industry Report (massolution, 2013) the total funding volume of crowdfunding platforms was \$2,700 million in 2012. It almost doubled for two years in a row (\$1,441 million in 2011, \$824 million in 2010). Crowdfunding is employed by a variety of actors: artists who look for money for the next creative work, social projects looking for support, as well as business ventures. Hence, we use the term entrepreneur in a broad sense. It encompasses a business venture in the traditional sense, as well as an artist or a non-profit organisation.

existing transactions data from October 2010 to February 2014 consisting of 102,405 pledges and 2,711 projects. User names have been encoded, that is, they are anonymized but still identifiable.

This data set allows us to perform an analysis of pledges to projects over time. The key result about the funding dynamics is that success tends to come at a relatively late stage of the funding duration. The majority of projects (59%) that eventually get funded are not on a successful track (based on the percentage of their funding target they reached divided by the normalized elapsed project duration) when two thirds of the funding duration has passed. Only 41% of eventually funded projects look like a success story already early during the funding phase.

Furthermore, we observe a spike of pledges towards the end of the project duration, in line with the aggregate pattern of pledges at Kickstarter as reported by Kuppuswamy and Bayus (2013). Our dataset allows us to show that this increase before the end is due to pledges to projects that already reached their funding target. It is not the result of a last minute rush to make still unfunded projects succeed.

Finally, our project-level analysis shows that a project's target amount and its duration are negatively correlated with its success, while quality indicators of a project's communication (number of pitch videos and blog entries) with its potential funders are success determinants. These results confirm Kickstarter-based findings of Mollick (2014) using data from Startnext, another donations/pre-selling crowdfunding platform. For a subset of the projects in our dataset we also include all the projects' reward levels in the analysis. We find that an enhanced presence of pre-selling rewards and of rewards that confer social image to the pledger is positively correlated with project success, while the provision of product-unrelated services is negatively correlated.

The paper is organized as follows. In section 2 we review the related literature. Section 3 describes our data. Results are reported in section 4 and section 5 concludes.

2 Related literature

2.1 Entrepreneurial finance and crowdfunding

Generally, in order to finance new or ongoing projects an entrepreneur can rely on own funds or she can turn to external financing (by banks, venture capital firms or angel investors). The relationship between the entrepreneur and external financiers is complicated by information asymmetries regarding the entrepreneurial project's quality (see Jensen and Meckling, 1976). Ex-ante it is unclear to the financier, whether investing into the entrepreneur and her project is a good idea. These information asymmetries (combined with cash constraints of potential entrepreneurs) may result in efficiency losses. Worthy projects would go unfunded, because financial intermediaries are unable to evaluate them effectively. As documented by, for instance, Cosh et al. (2009), entrepreneurs indeed face difficulties to secure funding

from the external finance options.

Crowdfunding provides an alternative option for entrepreneurs to raise funds externally. Belleflamme et al. (2014) define it in the following way: “Crowdfunding involves an open call, mostly through the Internet, for the provision of financial resources either in form of donation or in exchange for the future product or some form of reward and/or voting rights.”² Crowdfunding originated in the creative industries (music, movies), but nowadays entrepreneurs from a wide range of backgrounds have adopted it to finance their projects. Hemer (2011) distinguishes between the following forms of crowdfunding: crowd lending, crowd equity, crowd donations, crowd pre-selling.³ The first two can be regarded as the crowd analogies of the traditional financing instruments bank loan and venture capital. Crowd donations and crowd pre-selling bring interactions known from other environments to the entrepreneurial finance context. Crowd donations are unconditional payment pledges of funders given to the entrepreneur. While there is no obligation for the entrepreneur to give anything in return, often some kind of reward is given to crowdfunders who donated to the project. This reward can be in the form of acknowledgments, for instance, in the credits of the crowdfunded movie or a sticker/postcard of the project.⁴ Crowd pre-selling means that the entrepreneur promises to deliver early versions of the product/service for a specified price. Via this advance order the entrepreneur is able to make sure that a critical production mass is reached, before she has to commit to any production fixed costs. This advance ordering can be regarded as a test of the market potential (see, e.g. Moe and Fader, 2002), while it simultaneously funds the project to get off the ground. Crowd pre-selling can also be seen as a way for the entrepreneur to price discriminate between two groups: crowdfunders who purchase the product/service in advance (possibly at a discount) and regular consumers who purchase via the market after the project is successful (see Belleflamme et al., 2014). Furthermore, crowd pre-selling allows entrepreneurs to differentiate their product/service. The entrepreneur could offer different reward levels, say, a basic version and additionally more sophisticated premium or deluxe versions that would cost more.

Commonly, the interaction between entrepreneurs and the crowd is facilitated by a crowdfunding platform. Bradford (2012) distinguishes between donation sites, reward/pre-purchase sites, lending sites with/without interest, and equity sites. However, in practice borders between them are blurred. Donation sites sometimes also allow for rewards to be offered to donors and reward/pre-purchase sites may allow for pledges without a reward in return. According to Hemer (2011) the threshold pledge model is the

²Their definition leans on the work of Kleemann et al. (2008) on crowdsourcing, which can be seen as a broader concept crowdfunding is nested in. The journalists Jeff Howe and Mark Robinson coined the term crowdsourcing in the June 2006 issue of *Wired Magazine*.

³Belleflamme et al. (2014) propose a similar categorization. They distinguish between equity purchase, loan, donation or pre-ordering of the product.

⁴While at first glance it does not seem to be a good idea to base the funding of a project purely on voluntary components, there is in fact ample evidence from various contexts that people do actually pay voluntarily. They donate to charitable organizations, see List (2011) for an overview. They purchase products/services (restaurant visits, music, roller coaster ride pictures in a theme park, video games, hotel rooms, flowers, zoo visits) under pay-what-you-want schemes, see, for instance, Kim et al. (2009); Regner and Barria (2009); Gneezy et al. (2010). They also contribute money to institutions like museums or public radio that can be regarded as public goods.

predominant model for crowdfunding platforms that operate via crowd donations or pre-selling and it is also implemented for micro-lending and investment models that serve crowd lending and crowd equity. This model functions in an all-or-nothing style, that is, the platform and the entrepreneur agree on a targeted sum of money that must be reached within a specified time span. If this threshold is not reached, there is no flow of funds. Essentially, crowdfunders pledge to pay a specified amount, and only if the threshold is reached their promises get implemented.

2.2 Empirical studies on crowdfunding

The literature on crowdfunding is nascent but growing fast. In a recent literature survey, Moritz and Block (2013) review 92 studies in the fields of economics and law. Only few empirical studies of reward/pre-purchase platforms exist. Mollick (2014) extracted information from the Kickstarter web site and built a data set of 48,034 projects. Data is at the project level, that is, there is no information about individual transactions. His analysis suggests that personal networks (proxied by the number of facebook friends of the entrepreneur) and signals of high project quality (proxied by the availability of a video that describes the project and spelling errors in the project description) are positive determinants of project success. Project duration and a project's target amount are negatively correlated with success. Giudici et al. (2013) collect a sample of 461 projects hosted on 11 Italian crowdfunding platforms. They find that project success is positively correlated with individual social capital (proxied by the number of contacts on social networks). Also Kuppuswamy and Bayus (2013) study Kickstarter data. In addition to project level data they collect the number of backers of each project over time. Looking at the aggregate picture, they observe a decrease of backers after a busy starting phase and an increase of backers when the project deadline approaches. They also find that project updates tend to increase as the project deadline draws near. Relatedly, Xu et al. (2014) find that Kickstarter projects with updates have a higher success rate.

Dynamic aspects of funding behavior have been investigated by several studies of crowd-lending sites. Using data from peer-to-peer loan auctions at Prosper.com, Herzenstein et al. (2011) provide empirical evidence of strategic herding behavior. More previous bids increase the chance a lender bids on an auction. Zhang and Liu (2012) also analyze data from Prosper.com. They find that lenders observe peer lending decisions and use this information to infer creditworthiness of borrowers. This finding is confirmed by Yum et al. (2012). Analyzing data of the site Popfunding.com they conclude that lenders rely on their own judgment when reliable signals are available through the market but that they seek the wisdom of the crowd when facts about creditworthiness is limited. Generally, these studies associate a positive effect with herding behavior as it is correlated with subsequent successful performance of the loans.

Peer effects are also found at donation sites. Burtch et al. (2013) study a crowdfunding platform that supports journalists. The site enables prospective authors to pitch ideas for articles to the crowd in order to get the necessary money to investigate and publish. The platform guarantees to make all produced work publicly available, hence, the output is a public good. The authors constructed a data set (154 projects and 4,353 unique contributors) that incorporates contributions and web traffic statistics. Their results suggest that contributions are subject to crowding out as users contribute less when they observe others contributing more frequently. They also find that a pitch's exposure during the funding process is positively correlated with readership upon publication. Koning and Model (2014) conduct a field experiment at a donations platform (www.donorschoose.org). They varied the contribution size to randomly selected new projects (no, small (\$5), or moderate-sized (\$40)). When the first donation to a project was moderate-sized projects fare better, when it was small they fare worse than projects with no contribution at all.

Agrawal et al. (2011) analyze data from SellaBand, a platform that connects musicians who need money to produce their album and the crowd. They report that funders tend to invest in a project the more capital it already accumulated. They also look at the relationship between geographic distance and inclination to invest. While the average distance between bands and funders was circa 3,000 miles, they find evidence of a family and friends effect in the early phase of funding.

Finally, a handful of studies from computer science employs data about pledges over time (crawled from the Kickstarter website) in order to forecast project success. Given a project and its accumulated pledges at time t , the idea is to predict with some accuracy its success, or, at a higher level of detail, the final amount of pledges it will collect. Predictions are produced using existing data from all previous projects, or from similar projects only. In the former case, the predictor of a project success at project-time t is given by extrapolating from the project success of all previous projects at the same project-time t (an example using Markov chains is provided by Etter et al., 2013, using data from Kickstarter). In the latter case, the prediction comes from restricting attention to the N *most similar* projects in terms of characteristics to the projects that needs to be predicted, and then finding an appropriate weighted average of success rate of those N projects (examples are Etter et al., 2013; Greenberg et al., 2013). This last mechanism is at the core of crowdfunding-*prevision* websites such as Kickspy which offers a service to pledgers by computing 'project trends' from day one of a crowdfunding campaign. It turns out that the final outcome of a crowdfunding campaign can be predicted quite accurately analyzing the accumulated pledges at different points in time. The predictor of Etter et al. (2013) (based on pledges as well as social features) reaches more than 85% of correct predictions after 15% of the project's duration. Naturally, these approaches rely on the assumption that past average behavior of all or of similar projects is a good predictor of each and every new project. Consequently, prediction accuracy is quite good for

‘average’ projects, and quite bad for projects that are out of the trodden path.

To summarize, project-level analyses of reward/pre-purchase platforms (Giudici et al., 2013; Mollick, 2014) find that personal networks, respectively individual social capital, and signals of high project quality are success determinants, while project duration and a project’s target amount are negatively correlated with success. Looking at the dynamics of backers at a reward/pre-purchase site, Kuppuswamy and Bayus (2013) find a high volume of backers in the initial phase as well as towards the end of the project. While evidence from crowd-lending and donation sites indicates strategic rational herding among funders, it is unclear whether herding behavior plays a role at reward/pre-purchase platforms. Several studies on Kickstarter employ a data-driven approach in order to predict the success of a project at a relatively early point of a project’s duration.

3 Data Set

Startnext is the biggest crowdfunding platform in Germany (Crowdfunding-Monitor, 2014). It launched in October 2010. Its funding volume surpassed €500,000 in March 2012 and €1,000,000 in June 2012. By April 2014 it reached a funding volume of €10,000,000 and had 260,000 registered users. Startnext focuses on crowd donations and pre-selling (only in 2013 it introduced crowd investing), that is, its approach is similar to platforms like Kickstarter or Indiegogo. It employs the threshold pledge model. Hence, a project succeeds only if its pledges surpass the targeted amount within the funding duration of the project. If a project’s pledges amount to less than the targeted amount at the end of the funding duration, the project is not funded and pledges are not paid by users. Project owners can choose a funding duration between 10 and 90 days. In order to enter the funding phase projects have to reach a minimum level of fan support.⁵ One pledge to a project can consist of a donation and/or the commitment to purchase the project’s product/service. A project’s page at Startnext consists of its details (funding target, remaining time), a text description of what the project is about and a list of the reward levels in case of pre-selling. Additionally, the project owner can post a so-called pitch video, pictures or blog entries to provide more information about the project. The project’s current funding level as well as the number of supporters and fans are also accessible.

Our data set consists of all projects and all pledges made at Startnext since its launch in October 2010 until February 10th, 2014. This comprises a total of 2,711 projects, 459 that registered at Startnext but failed to fulfill requirements to enter the funding phase and 2,252 projects that made it to the funding phase. Out of those, 1,139 (or 51%) were successfully funded. We dropped a total of 13 projects (overall 84 pledges).⁶ For each project we collected the following variables:

⁵The number of required fans depends on the target amount of the project. It ranges from 10 required fans for projects with a target less than €500 to 100 fans for projects with a target higher than €7,500.

⁶Two projects asked for more than €100,000 but received only two, respectively seven, pledges and we decided to leave

Funding duration: Startnext allows project owners to specify the duration of their project’s funding phase as long as it is between 10 and 90 days.

Target amount: This is the amount project owners seek to raise.

Recommended: A dummy variable that indicates whether the project has been recommended (1) by Startnext or not (0).

Word count: The length of a project’s description in words.

Video count: The number of videos that users can view on a project’s page or its blog.

Image count: The number of pictures on a project’s page or its blog.

Blog entries: The number of entries on a project’s blog.

Categories: A set of dummy variables that indicate whether the project belongs to one of the 17 categories at Startnext (movie/video, music, event, theater, literature, art, photography, invention, journalism, design, cultural education, community, fashion, technology, games, audio drama and comic).

Table 1 contains summary statistics on the project level for all projects that made it to the funding phase (N=2,252). Overall, slightly more than half the projects that make it to the funding phase succeed. The average duration is two months, for an average target amount of nearly six thousand euros. Only 8% of projects get recommended on Startnext’s front page. The average project is described by a half-page text, features one video and 7 images; the project launchers blog about it roughly four times during the funding phase. The most popular project categories are movies (31.6%), music (25%), event (11.6%) and cultural education (11.1%).

Table 1: Summary statistics on the project level

variable	mean	st. dev.	min	median	max
project success	.506	.5	0	1	1
funding duration	58.02	24.87	5	57	90
target amount	5,700.19	11,304	100	3,000	290,000
recommended	.083	.276	0	0	1
word count	764.95	415.17	79	678	9,950
video count	1.09	2.31	0	0	27
image count	7.58	9.44	0	6	346
blog entries	3.97	4.59	0	3	50

Furthermore, for each pledge we have the following data:

Pledger anonymized ID of the person making the pledge.

them out of the analysis. For eleven projects the time stamps were not consistent. Moreover, due to our focus on crowd donations and pre-selling the two investment projects in the data set were not considered.

Date and time: the moment when the pledge was submitted.

Amount: Amount pledged, subdivided by pledge-level chosen.

IsDonation: A dummy variable that indicates if the pledge was a pure donation - i.e., without prizes, products, or services in return.

IsPreSelling: A dummy variable that indicates if the pledge (or part of it) was a pre-sale.

This allows us to identify projects and users in our data set (actual user names have been anonymized) and to index pledges both from the user and project perspective. Overall, 102,405 pledges have been made by 77,201 different users. The highest number of pledges by the same user is 109. The average number of pledges made per user is 1.32. The project with the most pledges received 3,126. On average, projects got 45.47 pledges. Generally, the majority of pledges (83%) is pre-selling, that is, the user receives a specific service or product in return for the pledge (if the project succeeds). About 19% of all pledges are donations. This value is a lower bound, since some of the reward levels include simple or elaborated ‘thank you’ messages from the project launchers. A detailed analysis of the reward levels will be carried out in section 4.2.

About 2.5% of all pledges are both a donation and a pre-sale.

Table 2: Summary statistics on the individual level (102,405 pledges)

variable	mean	st. dev.	min	median	max
Pledge amount	60.87	241.25	0.1	25	25,000
IsDonation	.19	.39	0	0	1
IsPreSelling	.83	.37	0	1	1
Pledges per project	45.47	123.37	1	19	3,126
Pledges per user	1.32	1.28	1	1	109

We also have data about the *fans* of each project. For a user, being a project’s fan implies a public support to the project with no financial consequences. We know the specific time a user became a fan of a project which allows us to compute the total number of fans of each project. Overall, 158,019 different users became a fan. The majority of them are fan of one project. The ‘biggest’ fan is a user who supported 328 projects. The average project gathered support from about 80 fans. The project with the highest fan support attracted 3,589 fans.

Table 3: Summary statistics of the fans data (226,045 observations)

variable	mean	st. dev.	min	median	max
Number of fans per project	79.64	124.54	1	58	3,589
Number of projects users are a fan of	1.47	3.22	1	1	328

4 Results

Our analysis consists of two parts, one on the project level and one on the individual level. We begin with an investigation of what determines the success of projects. This is based on projects' overall characteristics and complemented by an analysis of the offered and actually chosen reward levels. Then, we explore the dynamics of projects' funding using the pledges data.

4.1 Success determinants of projects

In order to get funded at Startnext, projects first have to attract a minimum level of fans during a so-called starting phase. If they reach the required level of fan support, projects enter the funding phase in which they can collect pledges.

Hence, we begin our analysis with the starting phase. Table 4 column I presents the results of a probit regression. Its dependent variable is whether a project makes it to the funding phase (1) or not (0). We find a negative correlation between a project's funding target and making it out of the starting phase. Moreover, attracting the required number of fans is also correlated with the word count of a project's description as well as the number of videos and images of a project. The project categories music and movies are negatively correlated (at the 5%-level), the categories games, invention, technology are positively correlated with success in the starting phase.

Table 4: Success determinants in the starting and funding phase

	I: starting phase		II: funding phase	
	coeff.	st.error	coeff.	st.error
Target amount	-.00003	.00001 **	-.0003	.00002 ***
Funding duration	–	–	-.0074	.0014 ***
Word count	.0002	.0001 **	.0001	.0001
Video	.3325	.0469 ***	.0539	.0167 ***
Image	.1038	.0104 ***	.0047	.0027 *
Blog entries	–	–	.0733	.0088 ***
Total fans	–	–	.0231	.0014 ***
Recommended	–	–	1.2	.2285 ***
Category dummies	yes		yes	
constant	.0229	.0896	-.6457	.118 ***
Pseudo R^2	0.17		0.33	
N	2,711		2,252	

significance levels: *** = 1%, ** = 5%, * = 10%

We proceed with a probit regression of all projects that made it to the funding phase, see table 4 column II. The dependent variable of this specification is whether a project has been successfully funded (1) or not (0).

The target amount of a project is negatively correlated with its success. Also the length of a project's funding period appears to have a negative effect on getting funded. Quality indicators of a project's

communication with its potential funders have by and large a positive impact. The number of videos and blog entries are significant at the 1%-level. The total number of fans of a project is positively correlated with the project's success as well as the dummy for being recommended by Startnext. Dummies for the categories invention, literature, design, games are negative and significant at the 5%-level. Only the dummy for the category music is positive and significant (5%-level).

Our analysis of Startnext projects' success determinants produces similar results to the study of Kickstarter projects by Mollick (2014). At both platforms it appears to be less likely for a project to get funded, the higher the target amount and the longer the funding period. Moreover, at both platforms the perception of a project's quality seems to be a determinant of success. While we employ the number of images/videos and blog updates, Mollick (2014) uses the existence of a project pitch video, quick updates and spelling errors in project pitch descriptions as quality measures. All are correlated with project success.

4.2 Analysis of reward levels

We complement the basic analysis of project success with a more detailed analysis of reward levels. The amount to be pledged at Startnext is free for the user to decide. Nonetheless, project launchers often provide rewards, i.e., products or services that are promised to the pledger in exchange for her donation, and that are delivered for a certain amount pledged in case the project succeeds. Projects differ in the number of levels offered, the amount needed and the nature of the reward associated with each level.

A typical project features 'cheap' levels entailing a thank you note or a small gadget, 'medium' levels providing the pledger with the full product, or with invitations to special events or with more elaborated gadgets (notably brand clothing), and 'expensive' levels with exclusive or all-comprehensive offers. Levels can be, and usually are, nested, with the more expensive level including the same rewards of cheaper levels, plus some extra reward.

The level structure was not included in the original Startnext dataset. In order to carry out the reward level analysis, we gathered information directly from the website of individual projects, and we merged the data with our project level variables. Since the procedure of identifying and coding the different levels was done manually, we identified a subset of 260 random projects, roughly one project in ten, and we restricted the analysis to this random sample.

For each project belonging to our random sample, we collected all the reward levels and the corresponding amounts needed to unlock the reward. We then coded the reward levels according to two criteria. First, an objective criterion, indicating the *nature* of the reward. We imposed five different possible natures for each reward: a simple thank you, pre-selling of the main product object of the crowdfunding campaign (a record, a movie, a comic book, a 3D-printed object, etc.), an unrelated service

(dinner, meeting, personalized lesson, etc.), an invitation (to the production or showcase or other event), or clothing (tee-shirts, baseball caps, badges, etc.). Second, we categorized the rewards with respect to the *visibility* of the pledger’s support. When surveying the crowdfunding landscape Belleflamme et al. (2014) conclude that “the crowd must identify themselves as such.” This community feeling of crowd-funders is often supported by rewards that strengthen the relationship between crowd and entrepreneur. We classify these rewards as enhancing the *self-image* of the pledger as a member of the community. Examples of self-image rewards are project-related souvenirs and specialized services/products meant only for the pledger. Crowdfunding projects could also use their reward structure to create additional appeal for funders who would like to show their support to others. Such rewards would target individuals who care about their social image and have a willingness to spend if their social-image benefits from the support. Likewise, being able to use/wear/consume new and innovative products/services – and show this to others – may translate into willingness to spend. Examples of social-image rewards are special thanks at the end of a movie, personalized web banners to be added to websites, brand clothing. Hence, we distinguish between rewards that potentially provide a boost for the self- or the social-image of the pledger, or both.

We exploit the reward level data and the classification we imposed on them running two different analyses: a supply-side analysis of the impact on project success of *offering* certain rewards over others; and a demand-side analysis of the impact of the actual choices of rewards by pledgers. The results of these analyses are in Table 5.

The Table first replicates (column 1) the project-level analysis of Table 4, finding by and large results consistent with the latter analysis on a much smaller sample of $\sim 10\%$ of the full dataset. The second column reports results of the supply-side analysis. Offering a higher share of social-image rewards is correlated (at 10%) with project success. The nature of the rewards offered also matters: pre-selling, invitations and brand clothing are correlated with success, while offering unrelated services has a negative impact. The third column reports the results when the actual choices of pledgers are taken into account, rather than just the offered rewards. Results show that successful projects tend to have disproportionately more pledges related to social-image concerns, and to pre-selling and clothes rewards.

4.3 Analysis of funding dynamics

For our analysis of funding dynamics we normalize the funding duration of projects as well as their target amount. All projects start at *project time* 0 and end at 1 which means that independently of the actual funding duration (which could be between 10 and 90 days) a pledge given at the, say, halfway mark of the project is given at 0.5 of our virtual project duration. Likewise, for each pledge to a project we compute the ratio of cumulative pledges to a project’s target amount. If this *funding ratio* equals 1 the

Table 5: Success determinants, impact of pledge levels proposed

	Basic analysis		Offered levels		Chosen levels	
	coeff.	st.err.	coeff.	st.err.	coeff.	st.err.
Target amount	-0.000341***	(0.0000618)	-0.000375***	(0.0000668)	-0.000328***	(0.0000652)
Funding duration	-0.0111**	(0.00445)	-0.0153***	(0.00507)	-0.0137***	(0.00493)
Word count	0.0000714	(0.000374)	-0.000117	(0.000415)	0.000119	(0.000417)
Video	0.138	(0.109)	0.125	(0.115)	0.160	(0.119)
Image	0.0464*	(0.0248)	0.0504*	(0.0276)	0.0459*	(0.0277)
Blog entries	0.0888***	(0.0325)	0.127***	(0.0382)	0.0894**	(0.0350)
Total Fans	0.0393***	(0.00635)	0.0462***	(0.00722)	0.0381***	(0.00680)
Recommended	0.0392	(0.644)	-0.035	(0.605)	0.006	(0.642)
Category dummies	Yes		Yes		Yes	
Constant	-1.655***	(0.442)	-3.026***	(0.809)	-2.355***	(0.680)
<i>Analysis of pledges levels</i>						
Number of levels			0.0216	(0.0291)	0.0107	(0.0291)
<i>Offered levels</i>						
Share self-image			1.073	(0.678)		
Share social image			1.721*	(0.942)		
Share both			-0.101	(0.669)		
Share thank-you			1.037	(1.682)		
Share product			0.782*	(0.438)		
Share service			-1.845**	(0.744)		
Share invitation			1.072*	(0.651)		
Share clothes			1.427**	(0.706)		
<i>Chosen levels</i>						
Share self-image					0.241	(0.505)
Share social image					1.296*	(0.754)
Share both					-0.0476	(0.533)
Share thank-you					-0.855	(1.001)
Share product					0.818**	(0.354)
Share service					-0.403	(0.747)
Share invitation					0.493	(0.603)
Share clothes					1.321*	(0.690)
N			260		254	
Pseudo R^2	0.41		0.47		0.44	

Standard errors in parentheses. Significance levels: *** = 1%, ** = 5%, * = 10%

project has reached its funding target amount and will be successful. This enables us to compute the relative funding level reached by each pledge in a way that is comparable across projects.

Figure 1 shows a histogram of the *project time* of all pledges made. We chose to display data in 60 bins, since the average funding duration is of 60 days. That is, for the average project, a bar represent the amount of pledges received in a day. A quarter of all pledges were made within the first 10% of the project duration. Also towards the end of the project duration noticeably more pledges are made, with a spike in the last week. This aggregate pattern of pledges over time is in line with behavior at Kickstarter as reported by Kuppuswamy and Bayus (2013).

See figure 2 for a histogram of all projects' *funding ratio* reached at the end of the funding duration. The distribution features two peaks, one at zero or very little funding and one at a funding ratio of one or slightly above. Only few failed projects collected a substantial amount and, likewise, few successful projects attracted much more than the threshold they required to secure funding. This confirms the pattern reported by Mollick (2014) using Kickstarter data: crowdfunded projects tend to fail by large

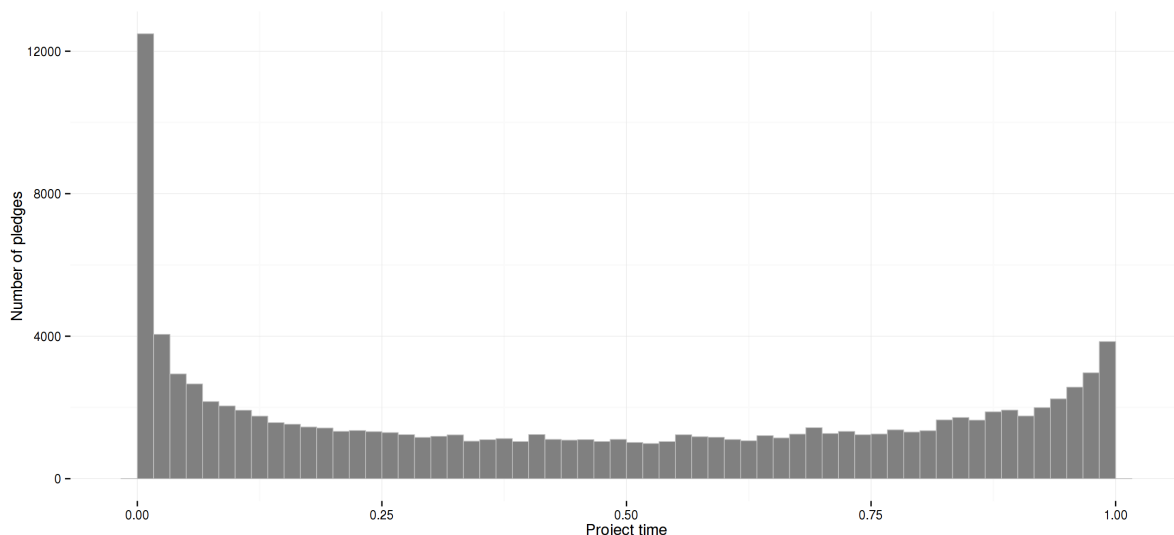


Figure 1: Distribution of pledges over the normalized funding duration

amounts and succeed by relatively small margins.

We proceed to categorize projects based on their dynamic funding patterns. For this purpose we distinguish between projects that are ‘on track’ to reach their funding target and those that are not. We make the simplest possible assumption of a linear trend in pledges. Since we know the elapsed time and the funding ratio for every pledge of a project we can compute the *relative funding level*: *funding ratio* divided by *project time*. A project is on track if its relative funding level is at least 1, while it is not on track if its relative funding level is below 1.

The initial phase of funding tends to be rather volatile and, hence, the relative funding level may not be meaningful in the beginning of a project’s funding period. Therefore, we look at projects’ relative funding levels in the second third of their *project time*. If the *relative funding level* of a project is at least 1 for every pledge made in the middle period of its funding duration, we categorize the project as on track. Likewise, a project is categorized as not on track, if its *relative funding level* is below 1 for every pledge made in the second third of its funding duration. This results in 280 on track projects and 950 that are not on track. For 251 projects the *relative funding level* switches between less than 1 and at least 1 during the middle period of its funding duration. We categorize them as ambiguous.

For some on track projects the label is technically correct but misleading since they already reached their funding target very early on. We use funding secured by the halfway mark of the *project time* in order to identify such projects (as *rockets*). In similar fashion some projects only collect very few pledges or none at all. Instead of not being on track they rather never make it off the ground. We categorize projects that never made it beyond 10% of their funding target as *failed* and this applies to 541 projects.

How meaningful is it for a project to be on track in the middle period? Among the 280 on track projects 265 eventually reach their funding target. Only 15 fade in the final third and fail to get funded.

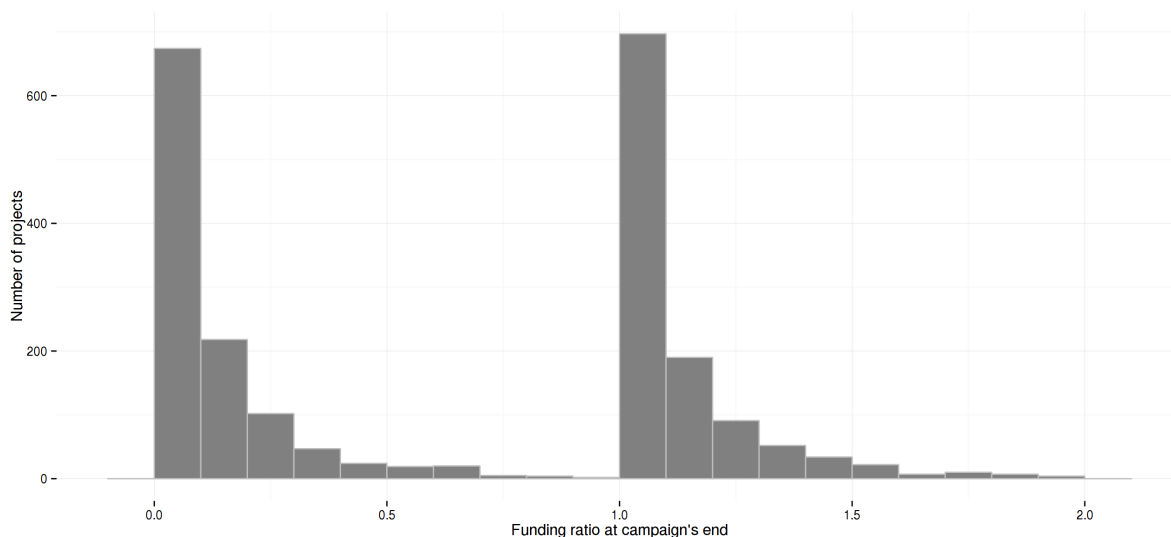


Figure 2: Ratio of cumulative pledges to targeted amount reached by projects (histogram is capped at a ratio of 2; 24 projects are cut)

Performance in the second third of funding time					
	failed	not on track	ambiguous	on track	rockets
Successful	–	510	242	265	93
Unsuccessful	541	440	9	15	–
All	541	950	251	280	93

Table 6: Dynamic project categorization

The eventual success of most on track projects confirms earlier findings. If a project is on a promising trajectory/path, its chances to receive funding are very high. The picture is different for the 950 projects that are categorized as not on track. While 440 of them eventually do not make it, 510 turn out to be successful in the end even though their *relative funding level* was always less than 1 before two thirds of the *project time* has passed. The picture of projects categorized as ambiguous looks very similar to the one of on track projects. Most of them (242 of 251) succeed. See Table 6 for an overview. A total of 137 projects could not be categorized using this approach, because they did not receive pledges in the second third of their project duration.

We can get into more detail using a data-driven prediction algorithm similar to Greenberg et al. (2013).⁷ The algorithm works on similarity: the predicted probability of success is the average of the probability of success of similar projects. Given a set of similar projects, the algorithm returns the average of the pledges collected at the end of the funding time, relative to the pre-set threshold. In our implementation of the algorithm, a project is considered *similar* to our target project if it has collected,

⁷Such an approach considers only similar projects instead of relying on the data from all previous projects at the same project time. Hence, it adds more assumptions, and combines them with data, to get more accurate predictions.

Performance in the second third of funding time		Predictions		
		Failure	Success	Total
Not on track	successful	329	181	510
	unsuccessful	421	19	440
Ambiguous	successful	1	241	242
	unsuccessful	1	8	9
On track	successful	1	264	265
	unsuccessful	1	14	15

Table 7: Results of the data-driven prediction algorithm at two thirds of project time

at two thirds of funding time, the same relative amount of pledges, plus or minus 2.5%. We classify a project as a predicted success if its predicted share of final financing at two thirds of funding time is greater than or equal to 1, and a predicted failure otherwise. The results of the prediction algorithm are reported in Table 7.

The algorithm is able to refine the findings for the large category of not on track projects, but only to a point. It correctly identifies most of the not on track projects that end up as failures; at the same time, it is not able to account for the bulk of not on track projects that eventually make it in the end: 329 projects are predicted as failures, despite turning out to being successful in the end. The overall prediction accuracy for not on track projects is 66.38%, up from a 46.3% (440/950) accuracy of simply predicting success/failure for not on track projects.

At the same time, the algorithm is too optimistic for ambiguous and on-track projects, doing slightly worse than the simple predictions based on the on-track property for ambiguous and on-track projects.⁸

The prediction algorithm does better than the simple classification we proposed above, but it is overly pessimistic for not on-track projects and overly optimistic for on-track ones. This is because the algorithm works on similarity and average project behavior. Outliers – projects not on track that end up passing the threshold, and projects on track that fail at the very end – cannot be accurately predicted.

This means that there is still hope for a relatively high number of projects (329 out of 950) that are not on track after two thirds of the funding span has passed. The fact that these project are able to secure the required threshold amount in the end might be indirectly linked with our previous results on the determinants of project success (that includes blog posts, videos, images on the one hand, and the presence of several product selling levels among those on offer): the launchers of these not on-track but in the end successful projects might have made an extra-effort at reaching a larger audience, or changed the reward levels of their project.

Figures 3 and 4 provide scatter plots of all pledges split by the project categories we have identified (*failed* projects that never make it off the ground are not shown). Figure 3 shows projects that are

⁸We do not report findings for failed and rocket projects, for which the algorithm predicts with perfect accuracy, because by definition there is nothing to predict (failures are already failed at their half life, rockets have already reached their threshold).

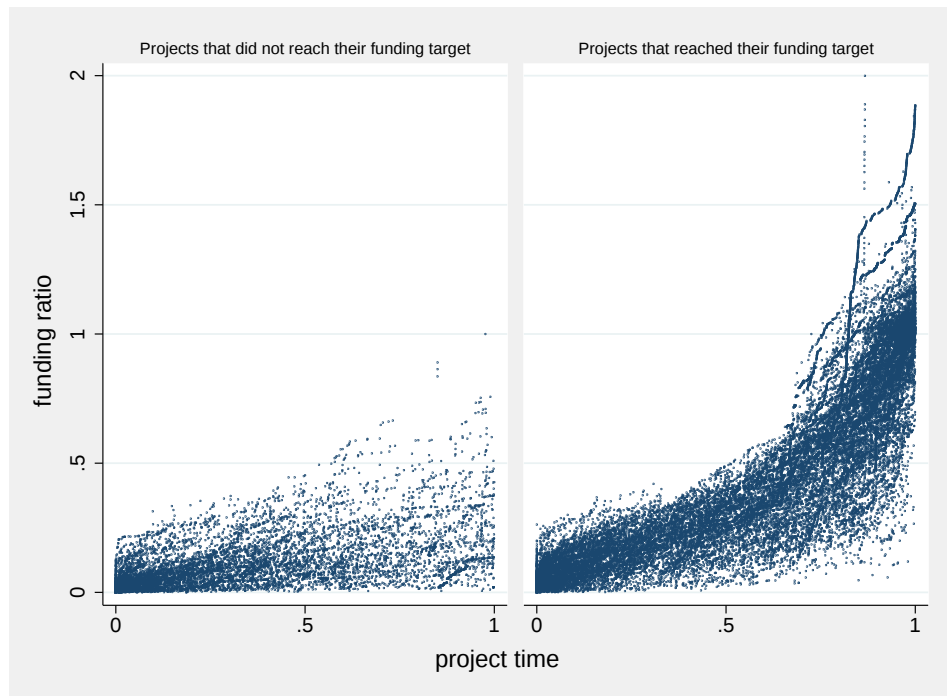


Figure 3: Scatter plots (funding ratio vs. project time) of not on track projects (capped at a funding ratio of 2)

categorized as not on track. This graphical representation of pledges over time illustrates that late bloomers (right plot) start slow but, in contrast to their counterparts that do not make it (left plot), get an eventual boost of pledges. For some projects the boost comes very late and when they are still far away from the funding target. This pronounced boost towards the end results in ‘exponential’ trajectories. Generally, projects that have been on track (figure 4) are on ‘linear’-like trajectories. Only very few of them (left plot) cannot follow through and fail to reach the target. The vast majority (middle) continues their promising path. Rockets (right) start on very high trajectories. Some reach their funding target extremely early. Pledges tend to become less over time resulting in ‘logarithmic’ trajectories. Besides these general trends it is worth to note that projects may feature pledge spikes before the end of the funding duration, independently of their category.

To summarize, our individual-level analysis of funding dynamics shows that relatively early in the life of a crowdfunding project eventual success can be predicted reliably by a linear trend indicator. However, this applies only to a relatively small amount of projects (about 30%). The majority of all projects do not look like they will get funded (at two thirds of the project duration): about 25% attract negligible amounts of pledges (and fail eventually) and about 45% cannot be considered on track. Nevertheless, half of those still make it in the end as they get a boost relatively late. A data-driven prediction algorithm based on project similarity is able to refine these findings. The algorithm performs well for not on track projects that fail eventually, correctly identifying most of them. However, many not on track projects

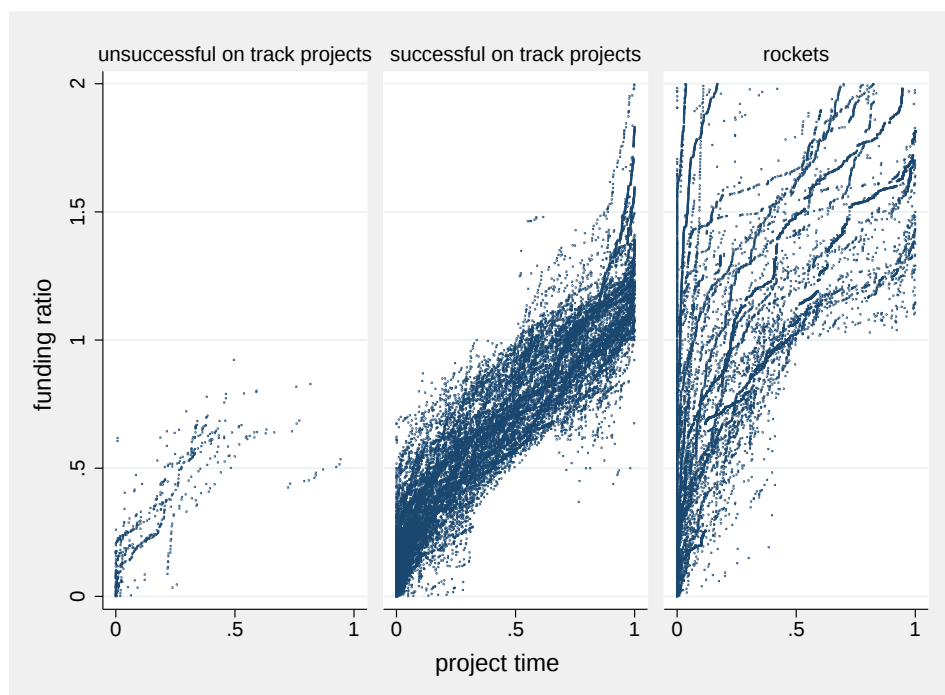


Figure 4: Scatter plots (funding ratio vs. project time) of on track projects (capped at a funding ratio of 2)

are predicted as failures despite succeeding eventually (329 of 510). The algorithm's prediction accuracy for not on track projects (66.38%) is better than 'eye-balling's accuracy (46.3%), but it seems that substantial unobserved heterogeneity remains.

4.4 Analysis of pledges

A striking feature of the scatter plots in figures 3 and 4 is that successful projects collect pledges after their funding target has already been reached. Overall, 18.7% of all pledges have been made when the funding target of the project had already been met. In our further analysis we look into this aspect in more detail.

Figure 5, top panel shows the distribution of pledges over project time taking into account whether the pledge is directed to a project that would eventually end up failing, to a project that would eventually succeed or to an already successful project, i.e., a project that at the time of the pledge had already met its funding target. As in figure 1 above, project time is broken down over 60 bins, indicating that a bin is one day for the average project. The bottom panel shows the same data, normalized to display relative shares. Naturally, projects that have not secured funding account for the vast majority of pledges in the starting weeks. However, after the initial phase of funding pledges stay on essentially the same level and there is no increase in pledges towards the deadline in order to get not yet funded projects over the threshold. Instead, the spike of pledges towards the end of project life is due to projects that

already made it. At the same time, pledges to project that will eventually fail disappear, as it becomes increasingly clear that a project is bound to fail. During the last 10% of project time about 60% of pledges made actually go to projects that already reached their target. In the last (average) day this accounts for more than 75% of all pledges.

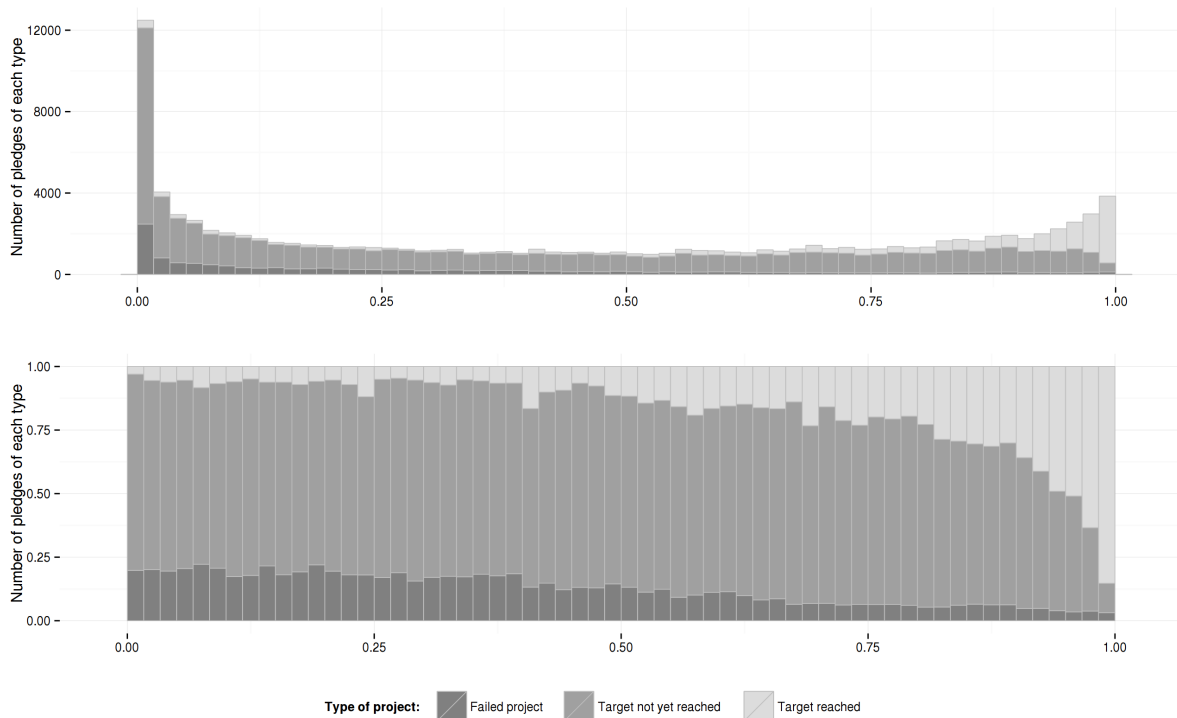


Figure 5: Count of pledges over time, by type: pledges to unsuccessful projects, to projects already funded, to projects still below their target amount

When a project has already reached its funding target, 16% of the pledges are donations and 86.5% are pre-selling. In comparison to before the target was met donations become less frequent (Fisher exact test, $p < .01$) and pre-selling becomes more frequent ($p < .01$). Hence, there is a tendency that crowdfunders purchase products/services from projects that already secured funding. In contrast to earlier in the project life when funding was not guaranteed the crowd now knows that the project is successful and the transaction is a straight purchase, possibly at a discount compared to the future retail price of the crowdfunded product, not the somewhat risky combination of potential purchase and support in funding. Nevertheless, the spike of pledges towards the end of the funding duration can also be observed for donations, although to a much smaller extent. Donating to a project that has reached its threshold means paying for sure while the project is successful anyway. It appears that the crowd, at least partly, just wants to be a part of a successful project.

5 Discussion

Crowdfunding experienced exponential growth over the last years and can be regarded as an alternative to traditional financiers of entrepreneurs, like banks, venture capital or angel investors. We received individual-level data from Startnext, the biggest crowdfunding platform in Germany. This dataset consists of all existing transactions from Startnext’s launch in October 2010 until February 2014. To the best of our knowledge, it is unique in the crowdfunding literature as we have direct access to the data of a major donations/pre-selling crowdfunding platform. This dataset allows us to investigate the dynamics of pledges and explore the motivations of pledgers.

Our analysis confirms that relatively early in the life of a crowdfunding project eventual success can be predicted (see also data-driven studies like Etter et al., 2013; Greenberg et al., 2013), but it also shows that a substantial amount of projects that are not predicted to reach their funding target (at two thirds of the project duration) still make it in the end. Overall, about 30% of all projects collect enough pledges early on to appear on track and most of them keep the momentum going until they succeed. About 25% do not get more than a negligible amount of pledges and fail. About 45% attract pledges but do not seem on track to succeed. Half of those indeed fail to get eventual funding, while half of them manages to get a boost relatively late and they succeed. A substantial amount (18.7%) of pledges is made to projects that already reached their funding target. This funding of already successful projects accelerates towards the end of the funding duration resulting in a spike of pledges before the deadline. This spike is due both to pre-selling and donations, but pre-selling becomes significantly more frequent after a project’s target is met. Overall, we observe a spike of pledges at the beginning and towards the end of a project, in line with Kickstarter data as reported by Kuppaswamy and Bayus (2013). However, this U-shaped pattern of pledges over time is an aggregate level characteristic that does not necessarily hold for all projects. Looking at individual projects and their funding dynamics, we can distinguish several funding patterns: eventually successful not on track projects exhibit an ‘exponential’ trajectory with a pronounced pledges boost towards the end; on track projects have a ‘linear’-like trajectory; rockets reach their funding threshold already early on and feature a ‘logarithmic’ trajectory. Moreover, results from our project-level analysis confirm Kickstarter-based findings of Mollick (2014). At Startnext, a project’s target amount and its duration are negatively correlated with its success, while quality indicators of a project’s communication (number of pitch videos and blog entries) with its potential funders are success determinants. Finally, for a subset of the projects in our dataset we also analyzed the role of projects’ reward levels. Project success is positively correlated with a higher presence of pre-selling rewards and of rewards that provide social reputation to the pledger, while it is negatively correlated to the provision of not product-related services.

Taking together insights from the related literature and our findings, we put forward two conjectures:

successful communication matters to kickstart crowdfunding projects, be it early or late in a project's life; pre-selling is instrumental for crowdfunding success.

Quality indicators of projects' communication are correlated with project success at Startnext and at Kickstarter as established by Mollick (2014) who also finds that the number of facebook friends is correlated with project success. Our analysis of funding dynamics shows that projects can get boosted to eventual success at virtually any point of time. While our data does not allow us to connect the increase in pledges to specific communication efforts (e.g. an update of the project's blog, a post in a social network), it seems plausible that such efforts trigger the pledges boost.

We generally find that a higher presence of pre-selling rewards is a determinant of project success. Specifically, projects that feature social-image rewards, allowing pledgers to show their support publicly, tend to be more successful. Furthermore, our analysis shows that the spike towards the deadline is due to pledges to projects that already reached their funding target. During the final 10% of projects' duration about 60% of pledges were made to projects that already secured funding. Making still unfunded projects succeed does not seem to be the motivation for 'last minute' pledges. Instead, our analysis shows that pre-selling drives pledges when a project's target was met already.

Seen in the light of our results, crowdfunding at donations/pre-selling platforms appears, foremost, to be a clever way of selling and simultaneously securing necessary funding to cover production costs. Our results also indicate that there is some truth in the widespread belief that crowdfunding is tapping into some hidden reservoir of altruism present in internet communities (Palmer, 2014). A consistent share of pledges are outright donations, even *after* a project reached its funding target. However, pre-selling is dramatically more central to project success than donations are. Offering pre-selling rewards correlates with success, product pre-sales are chosen more often than other types of rewards, and pre-selling enables entrepreneurs to offer rewards that appeal to pledgers' social-image concerns.

The literature on crowdfunding is still in its infancy. Our study complements existing research on crowdfunding projects' success determinants. It contributes to a better understanding of funding dynamics. Finally, it provides some insights about the motivation of pledgers. More research, both using observational data and via controlled experiments, is surely needed to assess in detail the determinants of pledges at the individual level. Our study may provide useful input for such future research on crowdfunding.

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