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It's never too late: Funding dynamics and self pledges in reward-based crowdfunding[☆]

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ABSTRACT

Crowdfunding recently emerged as an alternative funding channel for entrepreneurs. We use pledge-level data from Startnext, the biggest German platform, to gain insights on funding dynamics and pledgers' motivations. We find that the majority of projects that eventually succeed are not on a successful track at 75% of their funding period. These late successes are boosted by information cascades during the final 25% of the funding duration. We conclude – in contrast with earlier literature – that project success is only partially path-dependent. While early pledges do anticipate project success, a lack of them does not necessarily mean that projects will fail. Interviews and questionnaire responses indicate that projects' communication efforts play a role in making severely under track projects succeed eventually. Moreover, our dataset uniquely allows us to quantify the extent of self funding. Self pledges account for about 10% of all initial pledges and 9% of all pledges that secure funding. Nonetheless, the late surges at severely under track projects are mostly driven by external funders. Furthermore, we find no evidence of subsequent herding triggered by self pledges.

1. Introduction

One of the biggest challenges an entrepreneur faces is to get funding for her project. Crowdfunding recently emerged as an alternative funding channel for entrepreneurs. In contrast to traditional financiers, such as banks, venture capital firms or angel investors, crowdfunding allows individuals to fund entrepreneurs directly, even with extremely small amounts. Specifically, a mass of disconnected and independent individuals – the *crowd* – 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 entrepreneurs is often facilitated by an on-line platform. Entrepreneurs present their projects on the platform, alongside other projects. Users can browse several projects, get information and updates, and are provided with direct channels of communication with the entrepreneurs. Hence, users take individual decisions to invest/lend/purchase/donate, but fund as a crowd.

Crowdfunding experienced exponential growth in the last years and has now 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, essentially an advance order, and crowd donations introduce innovative interactions to the entrepreneurial finance context and are the focus of our study. Several successful on-line platforms offer crowd pre-selling and donations, with Kickstarter (www.kickstarter.com) being the most prominent example. 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. Individual donors pledge to support the project on the platform; their pledges turn into payments in case the project succeeds in reaching its funding target within the allotted time frame.

Several static aspects of what motivates the crowd to pledge have

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[1] According to the Crowdfunding Industry Report (massolution, 2016) the total funding volume of crowdfunding platforms was \$34.4 billion in 2015, up from \$16.2 billion in 2014, \$6.1 billion in 2013 and \$2.7 billion in 2012. 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 innovative 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.

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been identified: feelings of identity/community (Gerber et al., 2012), quality of communication (Beaulieu and Sarker, 2013; Mollick, 2014), the entrepreneur's social capital (Mollick, 2014), and altruism towards the entrepreneur (Gleasure and Feller, 2016a). The dynamics of funding behavior are less explored. Are crowdfunders affected by the funding decisions of others and to what extent is project success path-dependent, determined by very early pledges? Given that herding behavior exists, do entrepreneurs try to trigger information cascades themselves and, finally, are they successful in doing so?

Startnext, the biggest crowdfunding platform in Germany, provided us with anonymized data of all existing transactions from October 2010 to February 2014 consisting of 102,405 pledges over 2713 projects. These individual-level data enable us to investigate funding dynamics and explore pledgers' motivations.[2] Moreover, the data uniquely allow us to identify whether a pledge was made by the project creator him-/herself as Startnext does not prohibit nor sanction self-funding (in contrast to Kickstarter or Indiegogo). This allows us to quantify the extent of self funding, identify its role in the dynamics of project success and evaluate its impact.

With respect to funding dynamics, we find that success tends to come at a relatively late stage of the funding duration. The majority of projects (55%) that eventually get funded are not on a successful track when 75% of the funding duration has passed. Only 45% of eventually funded projects look like a success story already early during the funding phase. Further analysis of the funding dynamics provides evidence for information cascades during the first 10% of the funding period. While this is in line with early ‘success breeds success’ path-dependent patterns (van de Rijt et al., 2014; Colombo et al., 2015), we also find information cascades during the last 25% of the funding period. These late boosts seem responsible for the success of projects that did not look like they would get funded. Hence, a qualification of the general notion of path dependence appears warranted: while early pledges do anticipate project success, a lack of them does not necessarily mean that projects will fail. Qualitative insights, from interviews with Startnext staff and questionnaire responses from projects, indicate that projects' communication efforts play a role in making severely under track projects succeed eventually.

With respect to self funding, our analysis shows that self pledges account for 1.6% of all pledges. Despite this seemingly small role, we show that self pledges are substantial and important for projects' dynamics and eventual success. The distribution of self pledges clearly identifies three main motivations: to kick-start a campaign, to revive interest in a project after a period of slack and to secure funding. About 10% of all initial pledges are self-funded; and self pledges account for about 9% of all *pivotal* pledges (the pledge making a project pass the threshold). However, we find no evidence that self pledges trigger subsequent herding behavior, be it at the campaign's start or later in the funding process. We further show that some projects benefit disproportionally from self pledges: 6% of all projects are self funded by more than a quarter of their funding target.

Finally, our study contributes to an improved understanding of crowdfunding's emergence for innovation. Our results indicate that the discourse between a project and its community tends to increase the project's chances to get funded, while Stanko and Henard (2017) show that this conversation improves the quality of the future product (via ‘open search’) and the diffusion of the product (via activating ‘earliest adopters’). Overall, it seems that the possibility of dialogue between crowd and entrepreneur, a feature that distinguishes crowdfunding from traditional entrepreneurial finance channels, is beneficial for innovation.

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). 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, Beck and Demirguc-Kunt (2006) or 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 the form of donation or in exchange for the future product or some form of reward to support initiatives for specific purposes.” Crowdfunding originated in the creative industries (music, movies), but it has been adopted by entrepreneurs from a wide range of backgrounds. 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. 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. Belleflamme et al. (2015) distinguish between equity-, lending-, reward- and donation-based sites. However, in practice borders between them are blurred. Donation sites sometimes also allow for rewards to be offered to donors and reward-based sites may allow for pledges without a reward in return. According to Hemer (2011) the threshold pledge model is the predominant model for crowdfunding platforms that operate via crowd donations or pre-selling. This model functions in an all-or-nothing style, that is, the platform and the entrepreneur agree on a targeted sum of money that

[2] To the best of our knowledge, no study investigated single transactions data from a major reward-based crowdfunding platform (see Agrawal et al., 2014; Belleflamme et al., 2015; Gleasure and Feller, 2016b; Short et al., 2017, for recent surveys on crowdfunding). See Simons et al. (2017), Regner and Crosetto (2017) for studies that analyze the structure of reward levels and Beaulieu and Sarker (2013), Gleasure and Feller (2016c) for studies that look at funding patterns over time using qualitative methods.

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

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. Crowdfunding and innovation

As crowdfunding is establishing itself as a new funding channel for entrepreneurs several studies look at the impact of crowdfunding on innovation, beyond the mere fact that crowdfunding seems to be a remedy against underfunding of worthy projects. Gleasure and Feller (2016c), Mollick (2016) and Giudici et al. (2018) report case studies that document the relevance of community feedback. Stanko and Henard (2017) argue that crowdfunding impacts innovation via 'open search': pledgers actively contribute to the innovation process by providing feedback/ideas. They analyze technology-related projects from Kickstarter and find that the number of a project's pledgers and open search depth (drawing intensely from external sources) are positively correlated with later market performance. Their results also show that open search breadth (drawing from many external sources) leads to a focus on radical innovation in subsequent efforts of the project. Relatedly, Chan and Parhankangas (2017) find that – from the outset – campaigns tend to aim for incremental instead of radical innovations. Hence, the positive effect on radicalness of innovation appears to come from the interaction between creator and crowd.

Furthermore, crowdfunding has the potential to boost the diffusion of innovations via word of mouth (Stanko and Henard, 2017). Reward-based crowdfunding platforms can be regarded as a marketplace for products or services that are not yet on the mainstream marketplace. Thus, pledgers of a product or service can be viewed as the earliest possible adopters which would make them even more valuable than traditional early adopters in terms of spreading the word about the product (Scholz, 2015).

What about the longer term impact of crowdfunded projects? The results of Stanko and Henard (2017) show that the number of pledgers significantly impacts subsequent market performance of the crowdfunded product, while the amount of funding raised during the campaign does not. Roma et al. (2017) study the likelihood of successfully funded technology projects at Kickstarter to attract subsequent funding from professional investors. Their findings show that a higher pledged amount in the campaign is correlated with getting follow-up funding (given the presence of patents or a large social network). Based on a survey of Kickstarter projects Mollick and Kuppuswamy (2014) report that over 90% of successfully funded design/technology/video games projects remain ongoing ventures one year after funding and 32% generated yearly revenues of over $100,000 a year.

Finally, Mollick and Robb (2016) argue that crowdfunding democratizes access to the capital needed to develop and commercialize innovation. They show that in terms of geography crowdfunding is more evenly distributed than funding via venture capital. Moreover, they illustrate how crowdfunding facilitates access to funding for groups that are under-represented in obtaining capital from traditional financiers (like women or minorities).

2.3. Empirical studies on crowdfunding

The literature on crowdfunding is nascent but growing fast. Gleasure and Feller (2016b), a recent multidisciplinary review of the crowdfunding literature, distinguish between different types of funding behavior. According to them, pledgers at reward-based platforms are motivated by *financial or material benefits* (besides non-monetary motivations like *paying for social benefits* or *paying to participate*, see, e.g., Gerber et al., 2012) and signals of project/entrepreneur quality are used as guidance whether to pledge or not. Mollick (2014), for instance, analyzes project-level data extracted from Kickstarter and finds that project duration and a project's target amount are negatively correlated with success. Moreover, his analysis indicates 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. Various other studies confirm that projects' communication measures are an important success determinant.[4]

Some studies investigate dynamic aspects of reward-based crowdfunding. In a field experiment, van de Rijt et al. (2014) study the effect of a pledge to a previously unfunded project at Kickstarter. In comparison to a control group they find significantly higher success rates of treated projects due to cascades of positive reinforcement. Colombo et al. (2015) use three months of Kickstarter data. They focus on the role of early pledgers in determining the success of crowdfunding campaigns and their analysis confirms that early support is an important antecedent of project success. Also Kuppuswamy and Bayus (2017) study Kickstarter data. In addition to project level data they collect the number of pledgers of each project over time. They find that pledger support increases as the project approaches its funding goal.

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. (2011a) 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. Their finding of rational herding 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. 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.

Vismara (2016) analyzes data from the UK platform Crowdcube and shows that early investors, especially those with a public profile, attract investors in the remaining funding period. Vulkan et al. (2016), using data from the UK platform SEEDRS, show that having a strong start is an important campaign success determinant. Hornuf and Schwienbacher (2017) investigate data from four German crowdinvesting platforms. They report that crowd investors react to the information provided by the startups and also regard investments by larger, more sophisticated investors as valuable signals.

Finally, a handful of studies from computer science employ machine

[4] Kickstarter projects with updates have a higher success rate (Xu et al., 2014). The use of structural as well as narrative elements in the project presentation increases the chances of a positive outcome (Frydrych et al., 2016). The extent of exchange between creator and pledger in the project's forum is positively correlated with funding success (Kromidha and Robson, 2016; Wang et al., 2018). The project description's language matters for funding success (Gafni et al., 2017). Social media usage (Twitter, facebook) increases subsequent funding (Borst et al., 2017).

learning tools to forecast project success. Given a project and its accumulated pledges at time *t*, these studies predict its success probability exploiting existing data from all previous projects (Etter et al., 2013), or from similar projects only (Etter et al., 2013; Greenberg et al., 2013). 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. This literature is mature and it spawned websites offering success predictions from day one of a campaign, such as Sidekick.

To summarize, most evidence from crowdfunding sites suggests that funders take previous funding as a positive signal for their own funding decision. Moreover, data-driven approaches based on Kickstarter manage to predict project success fairly well at a relatively early point of a project's funding duration. It seems that path dependence is an important factor at crowdfunding and the general understanding is that early pledges anticipate whether a project will succeed or fail. However, there is also some evidence that is not in line with herding behavior, see the findings of crowding out in a public good setting (Burtch et al., 2013) or the influence of goal proximity (Kuppuswamy and Bayus, 2017).

3. Data set

Startnext, launched in October 2010, is the biggest crowdfunding platform in Germany (Crowdfunding-Monitor, 2017). Its funding volume surpassed € 500,000 in March 2012, € 1,000,000 in June 2012, and € 10,000,000 in April 2014. As of December 2017 € 49,000,000 were funded. 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 creators can choose a funding duration between 5 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 creator 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 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 2713 projects: 459 that registered at Startnext but failed to fulfill requirements to enter the funding phase and 2254 projects that made it to the funding phase.[6] Out of those, 1139 (51%) were successfully funded.

A description of our project-level and pledge-level variables is provided in Table 1. 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. About 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 creators 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%).

The uniqueness of our dataset stems from the pledge-level data. We can anonymously identify projects and users in our data. This allows us 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. On average, projects got 45.47 pledges, while one project received 3126. Generally, the majority of pledges (83%) receive a specific service or product in return for the pledge (if the project succeeds). About 19% of all pledges are simple donations – no reward received. This value is a lower bound, since some of the reward levels include simple or elaborated 'thank you' messages from the project creators. About 2.5% of all pledges are both a donation and entail a reward.

Crucially, and differently from platforms like Kickstarter or Indiegogo, Startnext allows project creators to pledge to their own project. Such 'self pledges' account for 1.6% of all pledges. A practical reason why Startnext allows this is to provide a possibility to creators to pay in funds that they received offline, say at a funding event, for their project. Besides, Startnext argues that self funding would take place anyway (via friends), so it is better to make it transparent by design. While the Startnext data allow us to identify pledges made by the project creators themselves, we cannot rule out that other pledges might be indirectly linked back to the project creator, acting through secondary accounts or friends. In this sense, our analysis represents just a lower bound of the phenomenon of self pledging.

4. Results

The Startnext dataset allows us to shed light on two main aspects of crowdfunding: dynamics, including possible herding behavior, and self pledges, including their motivations, their interaction with the dynamics and their impact. Given the breadth of the issues covered and the still fresh state of the theoretical literature on crowdfunding, we do not set out to formally test hypotheses. Nonetheless, this section provides a theoretical roadmap underpinning our results.

The crowdfunding literature has identified some clear stylized facts about the dynamics of a campaign. Most evidence from crowdfunding platforms documents herding behavior: funding decisions are correlated with previous funding to a project. This is in line with the literature on observational learning (pioneered by Banerjee, 1992; Bikhchandani et al., 1992) that addresses how agents' choices are affected by observing the behavior of other agents. Given sequentiality of choices and uncertainty about the valuation, the influence resulting from the information gained by observing others may lead agents to follow other agents' choices, even if they contradict own private information.[7]

As a first step in the analysis, we hence ascertain whether the Startnext dataset follows commonly observed patterns. Thus, we check whether path-dependence exists in the early stages of funding (building on the evidence from Etter et al., 2013; Greenberg et al., 2013; van de Rijt et al., 2014; Colombo et al., 2015).

However, the conditions for observational learning are not only in place early on but at any point of the funding duration. Thus, there is no reason why potential pledgers should not continuously be looking for cues of project quality. They may take others' choices to pledge to a project as a sufficiently positive quality signal in order to pledge themselves, be it early or late. Hence, we check to what extent path dependence rules projects' success chances also at later points of the funding duration.

[5] The 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 € 7500.

[6] We dropped a total of 13 projects (overall 75 pledges). 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.

[7] Çelen and Kariv (2004) distinguish between information cascades and herding behavior. Individuals in a cascade necessarily ignore their private signal, while individuals in a herd may ignore the private signal. Since we cannot tell the two apart due to the lack of access to pledgers' private signals, we use the two terms interchangeably (as it is common in the literature). Note that herding behavior is not necessarily rational. In fact, people may disregard information redundancies in their decision making leading to excessive, and potentially harmful, imitation (Eyster and Rabin, 2014).

Table 1
Variables of our dataset.

Variable	Unit	Description	Mean	St. dev.	Min	Median	Max
Project-level variables							
Funding duration	Days	Freely chosen by the project creator between 5 and 90 days	53.96	20.99	5	54	90
Target amount	€	The amount project creators seek to raise	6194.25	23,927	100	3000	1,000,000
Recommended	Dummy	Project recommended by Startnext and featured on the home page (1) or not (0)	.083	.276	0	0	1
Word count	Integer	Length of a project's description in words	764.55	415.33	79	678	9950
Video count	Integer	Number of videos that users can view on a project's page or its blog	1.09	2.31	0	0	27
Image count	Integer	Number of pictures on a project's page or its blog	7.58	9.44	0	6	346
Blog entries	Integer	Number of entries on a project's blog	3.97	4.59	0	3	50
Categories	Dummies	A set of dummies for the 17 categories at Startnext[a]	–	–	–	–	–
Pledge-level variables							
Pledger	String	Anonymized ID of the person making the pledge	–	–	–	–	–
Date and time	String	The moment when the pledge was submitted	–	–	–	–	–
Amount	€	Amount pledged, subdivided by pledge-level chosen	60.87	241.25	0.1	25	25,000
IsDonation	Dummy	Pledge was a pure donation (1) without prizes or products in return, or not (0)	.19	.39	0	0	1
IsPreSelling	Dummy	Pledge (or part of it) received product or service in return (1) or not (0)	.83	.37	0	1	1
IsSelfPledge	Dummy	Pledge was submitted by the project creator (1) or not (0)	.016	.125	0	0	1
Summary variables							
Pledges per project	Integer	Total number of pledges to a project	45.47	123.37	1	19	3126
Pledges per user	Integer	Total number of pledges to any project for each user	1.32	1.28	1	1	109

[a] Movie/video, music, event, theater, literature, art, photography, invention, journalism, design, cultural education, fashion, technology, games, audio drama and comic.

In order to shed more light on the drivers of herding behavior, independently of how much funding time has passed, we perform two distinct yet complementary analyses. First, we conduct a quantitative analysis of self pledges. Project creators may be aware of the potential for herding, and hence use self pledges strategically trying to initiate a cascade, to kick-start/revive their campaign. Besides, they may pledge themselves in order to reach the funding target, thus guaranteeing the funding of their project, especially if the funding period approaches its end. Second, we obtain qualitative data from interviews with Startnext staff and a survey among selected projects. The survey focuses on a subset of projects with the most informative dynamics and aims to collect stylized facts about what might have triggered late funding boosts.

Finally, we jointly analyze herding behavior and self funding exploiting the pledge level of our data. We test econometrically in which phases of the funding duration herding actually occurs and to what extent there is an interaction between herding and self pledges.

4.1. 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 5 and 90 days) a pledge given at the, say, halfway mark of the project is given at 0.5 of the normalized project duration. Likewise, for each pledge to a project we compute the ratio of cumulative pledges to a project's target amount, the *funding ratio*. This indicator tells us for each point in time how far along the road to success (funding ratio $\geq$ 1) a project is, in a way that is comparable across projects.

At the aggregate level, the timing of pledges is characterized by a bimodal distribution. A quarter of all pledges are made within the first 10% of the normalized project duration, and a further spike is observed at the end of the project life. This aggregate pattern of pledges over time is in line with behavior at Kickstarter as reported by Kuppuswamy and Bayus (2015).

However, the bimodal distribution hides a large individual heterogeneity of dynamic funding patterns. Projects follow logarithmic, linear (with varying slopes), or exponential patterns. That is, success can be achieved early on, little by little, or at the very last minute. In order to shed some light on the funding dynamics, we categorize projects according to how they fare, at any given moment, with respect to the average successful project.[8] We characterize projects as being *on track* if they follow – within a 5% band – the dynamic path of the average successful projects, and *over* or *under* track if they are respectively out- or under-performing.

The average successful project starts fast, has a weak period lasting until half of the project duration in which pledges reduce their growth, and spikes in the end to reach beyond its funding target. We define a project as on track at time *t* if its funding ratio lies within a 5% band around the average project's funding ratio at time *t*.[9] Fig. 1 shows the share of those projects that eventually end up succeeding that are under, on and over track across normalized project time.

If projects were similar to the average project, then being below the average path at, say, three quarters of project life should be a clear predictor of failure. Moreover, if project dynamics were path-dependent, i.e. if "success breeds success" (van de Rijt et al., 2014), the path followed over three quarters of project life should be long enough to clearly spell failure for under track projects. Our data largely prove otherwise. A large share of eventually successful projects are not on track for most of their duration: many under-track projects are late bloomers.[10] This is especially striking since the average project itself is a late bloomer. At 75% of project life more than one project in two underperforms the average, yet eventually jumps upwards to reach success in the very end. As Fig. 1 shows, only after approximately 90% of project time the majority of successful projects are actually on/over track to succeed.

To allow for a finer analysis we split the under track category into three different subcategories: *slightly under track* projects are up to 10 percentage points away from the track; *under track* projects, 10–30 percentage points away; and *severely under track* projects, more than 30 points away. Moreover, we label as *rockets* the 94 projects that had reached success before half of project time, and we deem as *failed* the

[8] The performance with respect to the average successful projects has already been used to predict project success (Etter et al., 2013; Greenberg et al., 2013).

[9] In order not to penalize projects in the very end, we define our track as the minimum of the track of the average successful project and 1, thus effectively considering success as success and not deeming 'under track' a project that is at, say, 105% of its target in the last days but shy of the average 117%.

[10] The converse is not true, though: most failed projects fail from the very beginning, so that more than 95% of projects that eventually fail are under track after 5% of project time.

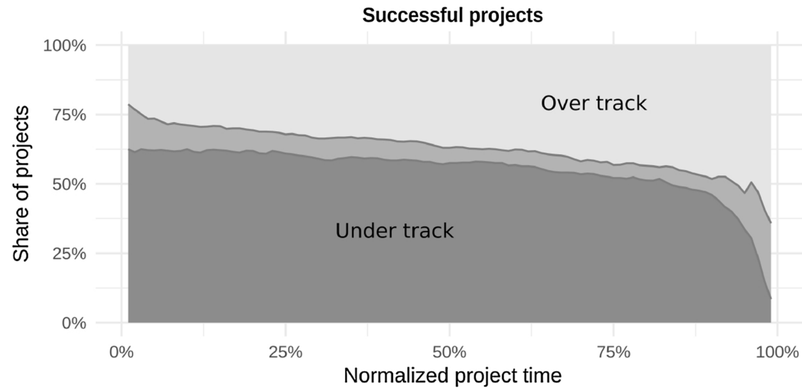

Fig. 1. Share of successful projects over, on or under track across project time.

Table 2
Performance with respect to data-driven track at 75% of project time.

	Failure	Success	Total	% Success	% Funded
Failed	674	–	674	0%	3.5%[a]
Severely under track (> 30%)	387	248	635	39.1%	106%
Under track (10–30%)	38	245	283	86.6%	111%
Slightly under track (< 10%)	9	130	139	93.5%	109%
On track	5	46	51	90.2%	107%
Over track	2	376	378	99.5%	117%
Rocket	–	94	94	100%	177%
Total	1115	1139	2254	50.5%	65.4%[a]

[a] *Not* conditional on success.

674 projects that never make it off the ground, never reaching more than 10% of their funding target over project time. Projects' performance with respect to this finer categorization is summarized in Table 2.

The data support path-dependence only partially: while being on or over track overwhelmingly leads to success, being under track is not an effective predictor of project failure. That is, success breeds success alright, but (initial) failure can lead to success, too. Only 0.5% (2 out of 378) of projects that outperform the average successful project at 75% of project time end up being failures, but an impressive 93.5% (130 out of 139) of slightly under track projects, 86.6% of under track and 39% of severely under track projects eventually succeed. Since the average successful project reached a funding ratio of 69.5% by three quarters of project time, this means that projects that reached as low as 39.5% of their funding ratio still have a 9 in 10 chance of succeeding, and that projects below that threshold (but above 10% funding) still have 4 chances in 10. The last column of Table 2 lists the average funding percentage (conditional on reaching the funding target). Tests of equality in distribution show that severely under track projects are different from the other categories (Kolmogorov–Smirnoff tests, $p < 0.01$), while the distributions of slightly under track, under and on track projects are not significantly different from each other (Kolmogorov-Smirnoff tests, $p > 0.12$). It seems that successful severely under track projects collect less funds than successful other categories. Note, however, that the amount of funding raised during a campaign does not seem to have an effect on subsequent market performance of the crowdfunded product (Stanko and Henard, 2017).

To shed further light on the dynamics of individual projects, Fig. 2 plots all pledges over time, according to the final outcome of the project (failure or success) and the on-track status at 75% of project time. The red line is the path followed by the average successful project, and the grey area around it is the on-track band.

Fig. 2 illustrates the large heterogeneity of dynamic paths across projects. Failed and successful under track projects share a similar slow start, but eventually successful ones experience a dramatic boost after 75% of project time, resulting for some projects in 'exponential' trajectories. On track projects show the expected inverse-S shape of the average successful projects; the few failed on/over track projects lose momentum towards the end of project life and do not get a boost in the last quarter. Among over track projects, some rockets reach their target early – most of them in the first quarter of project life – resulting in 'logarithmic' trajectories. It is worth noting that all eventually successful projects beside rockets share a surge in pledges in the last quarter of project life.

These dynamic patterns are strongly at odds with a generalized path-dependence interpretation of the data. Out of all successful projects, 33% were up to 30% off the average project and 22% were even more under track at three-quarters of project time. Fig. 3 allows us to better understand the nature of the late boom. It reports, for each dynamic category and for each of ten time intervals, the mean amount of each pledge received and the average number of pledges per project.

The overall means, over all time and all on-track categories, are 60.87 euro per pledge and 45.47 pledges per project (when translated into the 10 intervals, this yields roughly 4.5 pledges per project per interval). The different on-track categories show very different patterns. More specifically, in the last three intervals we see that severely under track projects do attract more pledgers than they did up to then, but that their number remains low compared to all other categories except failed projects; on the other hand, the *amount* pledged increases more than threefold in the last quarter of project life, from 53 to 177 euros per pledge, the highest amount recorded. These dynamics are peculiar to severely under track projects, and not shared by other less under track projects that keep the average amount roughly unchanged but increase two to fourfold the number of pledgers. These results suggest that severely under track projects fundamentally change their audience in the last quarter of their life, and that their observed late boom is due to generous last-minute donors rather than to having reached a wider audience.

Since Startnext allows self pledges – i.e., allows the project creator to directly pledge money to her own project – this result might be due to either the presence of external angel investors that pick among the lagging projects the ones they want to support, or that project creators pledge themselves over the threshold. We answer this question in the next section.

4.2. *Self pledges*

Self pledges account for 1.6% of all pledges. About one third of all project creators fund their own project, half of them self pledge only once. The distribution of self pledges over time is bimodal, concentrated at the beginning and end of a campaign. Descriptive statistics of self pledges are provided in Table 3, top. Generally, self pledges are in terms of amounts pledged about four times as big as common pledges. Self pledges tend to be made in a moment of inactivity: the mean time lag

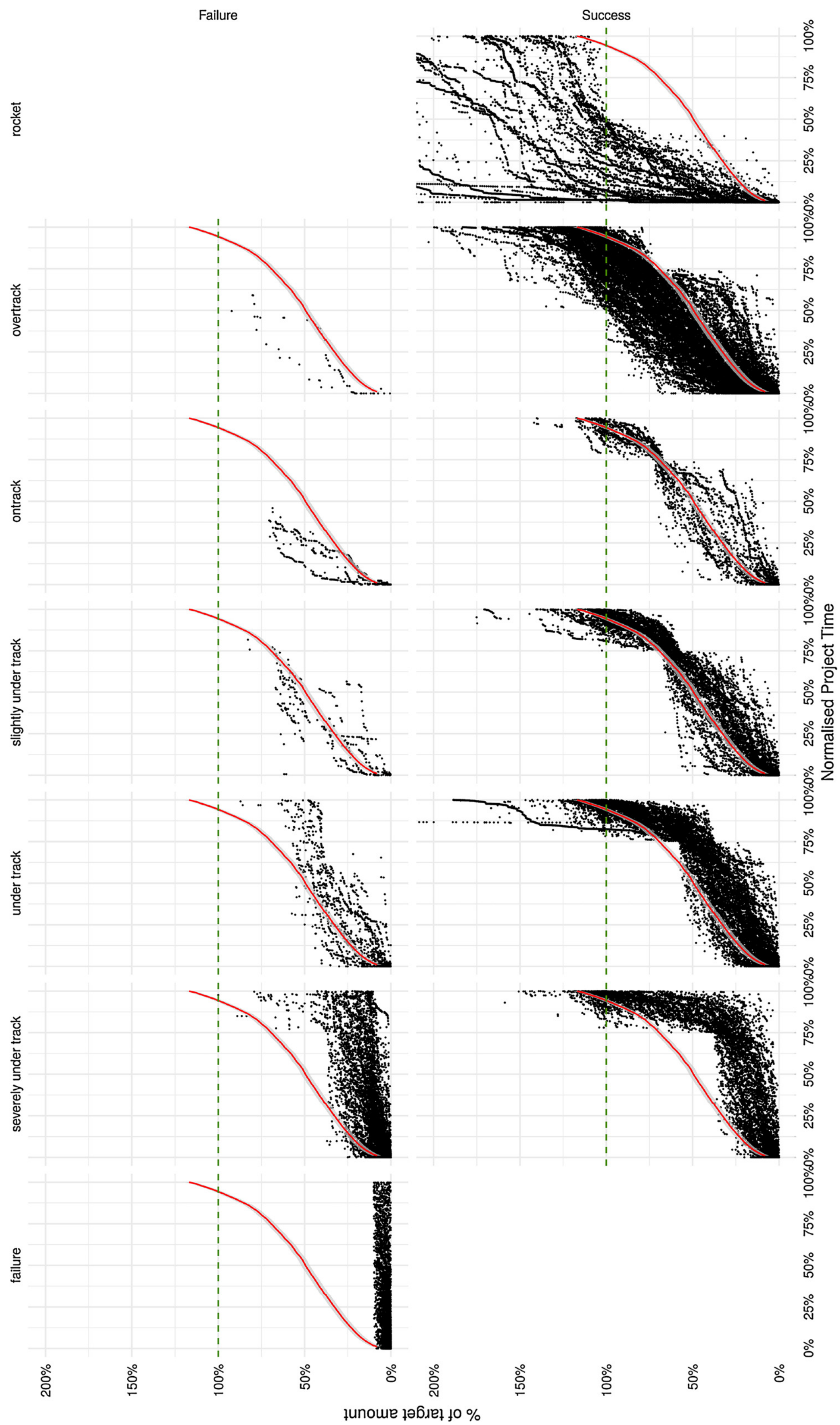

Fig. 2. Pledges over project time, classified according to the data-driven track at 75% of project time.

from the previous pledge is higher for self pledges than for common ones.

Based on the time of their occurrence during the funding process, we distinguish four types of pledges. First, self pledges might be the first pledge ever to be received by a project. Then, self pledges might be made during the campaign, 'in-between'. Sometimes it is a self pledge that actually pushed the project above the funding threshold: we call these self pledges pivotal. Finally, self pledges can arrive after the

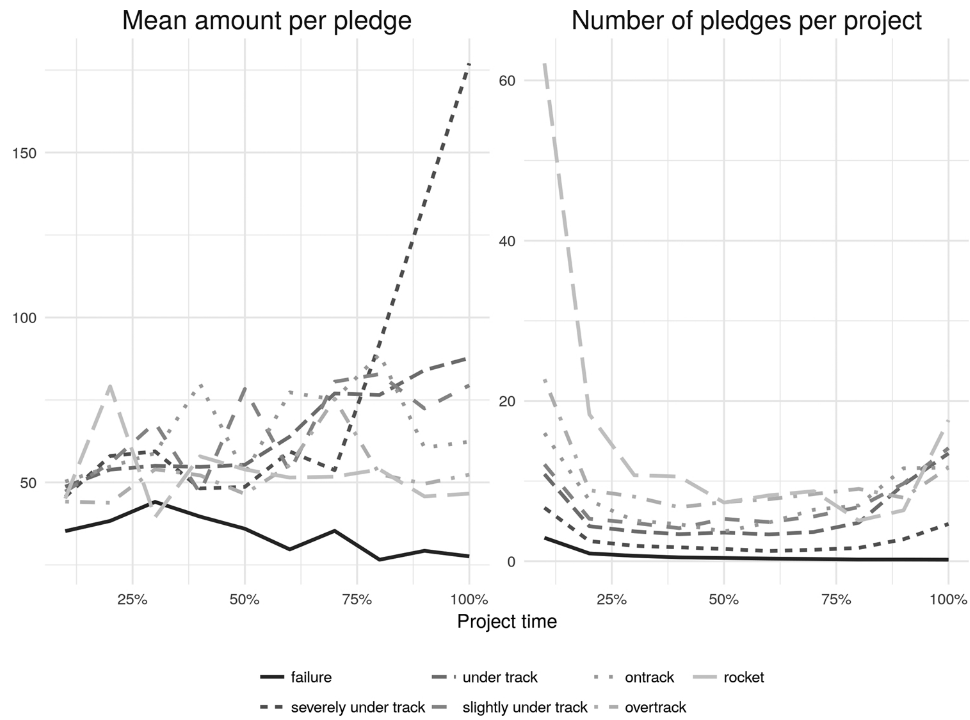

Fig. 3. Pledge amount and number statistics by project time and dynamic category.

funding target has been reached. Fig. 4 plots self pledges over time and funding ratio and by pledge type, and Table 3, bottom, provides descriptive statistics.

About 10% of all project creators start the funding of their campaign themselves. The average size of these self pledges is significantly smaller than the average size of first pledges by other users (ranksum test, $p < 0.01$). Out of all self pledges, 12.5% are used to start off funding to a project. 'In-between' self pledges account for the majority of all self funding. The average 'in-between' self pledge is significantly bigger and its time lag to the previous pledge is significantly longer than for their common counterparts (ranksum tests, $p < 0.01$). Its size tends to be more than 1% of the project's funding target which could be an indication that project creators intend to visibly increase their project's funding on the web site – which only shows integer changes. For 99 projects, a self pledge secured the project's funding. Such pivotal self pledges are, on average, bigger in comparison to the size of common pledges and also compared to other self pledge types (ranksum tests, $p < 0.01$). Finally, there are 113 self pledges after the funding target has been reached. Project creators may have wanted to push their project across the funding target but before they did a pivotal pledge to their project was made by someone else. Another explanation could be project funding that has been collected offline (at events, from supporters unwilling/unable to register online, say the grandma of the creator). These funds might be paid in when they accrue or, more likely,

Table 3
Descriptive statistics of self pledges by type and dynamic category.

		Pledge type				
		First	'In-between'	Pivotal	After target met	Total
N	Self pledges	203	1249	99	113	1664
	Common pledges	2051	80,813	1040	16,846	100,750
Mean €	Self pledges	32.23	208.56	474.77	108.48	196.06
	Common pledges	47.41	57	411.02	47.65	58.77
Mean time lag	Self pledges	–	.03	.028	.0166	.029
	Common pledges	–	.018	.026	.008	.016
By dynamic category						
Failed projects	Self pledge	84	67	–	–	151
	Self pledge share	12.46%	1.75%	–	–	3.36%
Severely under track	Self pledge	51	368	33	11	463
	Self pledge share	8.03%	2.47%	13.31%	1.8%	2.83%
Under track	Self pledge	23	349	24	14	410
	Self pledge share	8.13%	2.37%	9.8%	0.77%	2.40%
Slightly under track	Self pledge	16	168	15	13	212
	Self pledge share	11.51%	1.85%	11.54%	1.53%	2.08%
On track	Self pledge	2	55	7	14	78
	Self pledge share	3.92%	1.52%	15.22%	4.33%	0.93%
Over track	Self pledge	20	208	18	44	290
	Self pledge share	5.29%	0.73%	4.79%	0.71%	0.82%
Rocket	Self pledge	7	31	2	20	60
	Self pledge share	7.45%	0.43%	2.13%	0.28%	0.41%

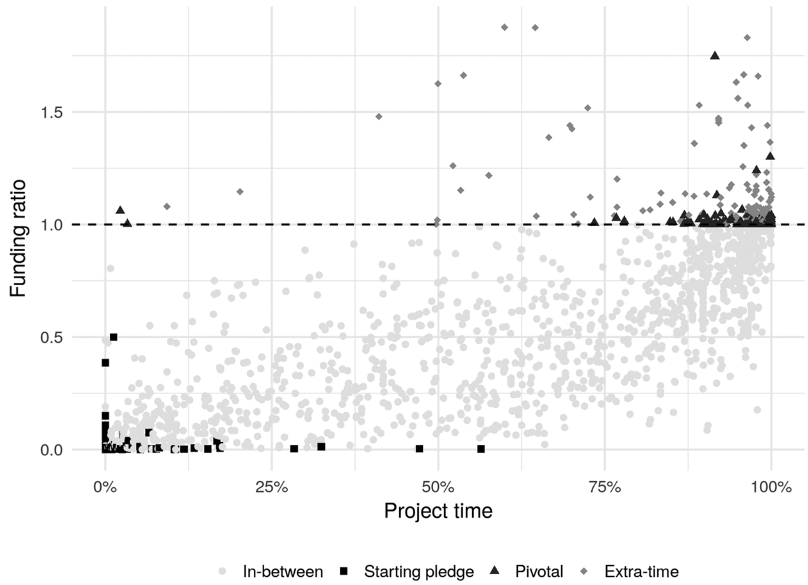

Fig. 4. Scatter plot of self pledges over time and by pledge type.

all lumped together towards the end of funding. The two projects that surpassed their funding target very early on via a self pledge are most likely examples for such (very successful) offline collections.

According to these patterns of use self funding is motivated by an indirect and a direct effect on overall funding. First, project creators may anticipate that users regard received pledges as a quality signal. Thus, they may try to initiate a cascade of pledges with their own pledge. Second, project creators may want to make sure that they get the funding for their project by pledging the amount that is still missing from reaching the target.

We first look at the direct effect of self funding: what is the role of self pledges, especially pivotal ones, in the late surges documented in Fig. 3? Generally, self pledges are more frequent in categories that seem furthest away from success: in fact, the proportion of self pledges is monotonically decreasing across project categories (Table 3, bottom, last column). By and large this pattern holds for pivotal self pledges: while they occur in under, on and over track projects alike, they are significantly more frequent among severely under track projects (13.31%) than among the rest (2.8%, chi square test, $p < 0.01$)

Excluding self pledges, the mean amount pledged to severely under track projects in interval 10 drops from 177 to 166, with 4.42 pledges per project, down from 4.65. This is still significantly higher than earlier intervals of other project types. The decreases for (slightly) under track projects and in intervals 8 and 9 are similar in size. Thus, the large majority of late funding to severely under track projects comes from external sources. It seems that there are indeed generous donors, angels in the crowd, who substantially support projects that look like they will fail.

However, some projects receive substantial self funding. While overall 693 project creators self pledged for, on average, 12.3% of their funding target, the 99 projects with a pivotal self pledge on average self-funded 29.8% of their target. About two thirds (68) already self pledged before making the pivotal one themselves (on average, 3.21 times). About half of them funded more than a quarter of their own project.[11] Overall, the direct effect of self funding is minor in comparison to the late-stage efforts of the crowd. Nevertheless, it is evident that around 6% of project creators helped themselves substantially to get their project funded. Given the nature of our dataset we are limited to identifying the extent of pivotal self pledging but we cannot evaluate its effect on the chances of a project to deliver what it promised. Thus, whether the influence of pivotal self pledges biases funding remains to be answered.

What our data permits is a limited analysis of project quality via a simple proxy: subsequent projects by the same project creator. It seems safe to assume that if a project failed to deliver its goods or services, then a subsequent project by the same person would have difficulties to attract funding. In our data there are 2110 first time projects (642 self funded, 1468 not) and 125 second projects. If the first project received at least one self pledge (52 times), the success rate of the second project is 71%. If it did not (73), it is 56%. Acknowledging the sample being limited, the proxy being fuzzy and the possibility that self pledgers may simply care more about their projects, there does not seem to be a negative effect of self funding on the likelihood to start another project nor on its success chances.

What is the indirect impact of self funding at the project level? We proceed to test the effect of self pledges on project success, controlling for other potential determinants. Table 4 column I presents the results of a probit regression on the first step – getting enough fans. Reaching the funding phase is correlated with lower target amounts, a higher word count and the presence of additional videos and images. Table 4 column IIa reports results of a probit on the second step – reaching the target amount. Our results by and large replicate established findings based on Kickstarter (Mollick, 2014), from several Italian crowdfunding sites (Giudici et al., 2013) and technology projects from four crowdfunding platforms (Cordova et al., 2015): smaller, shorter projects have higher success rates; higher efforts on communication as proxied by web site quantifiers pay off.[12] Moreover (not shown), music and movie projects have higher success rates, while literature, invention and technology projects have lower ones.[13]

In addition, our dummies for self funded projects show that an initial self pledge is negatively correlated with project success. In contrast, the number of in-between self pledges is positively correlated with eventual funding. A possible explanation could be that self-started projects tend to be of low quality. Actual quality of the project prevails as potential pledgers tend to get their evaluation right, despite the intervention of the project creator. Hence, a self pledge to start the

[11] Among self funded projects who did not make the pivotal pledge only 15% (88 projects) pledged more than a quarter, 86 of them reached their target.

[12] See Kaartemo (2017) and Butticè et al. (2018) for reviews of the literature on the success determinants of crowdfunding projects.

[13] See the Appendix for summary statistics by categories and a correlation matrix as well as variance inflation factors (all regressors are below the conventional cutoff of 10).

Table 4
Success determinants in the starting and funding phase.

	I: Starting phase		II: Funding phase					
			a: All		b: Severely under track		c: Under track or closer	
	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
Target amount (in 1000€)	−.0005	.0002 **	−.0231	.0042 ***	−.0337	.0085 ***	−.0012	.0004 ***
Funding duration	–	–	−.0035	.0005 ***	−.00001	.0008	−.0008	.0003
Word count (in 100)	.0056	.0021 ***	.0064	.0045	.0057	.0065	−.0016	.0008 *
Video count	.0526	.0095 ***	.0284	.0094 ***	.0344	.0119 ***	.0024	.0022
Image count	.0193	.0023 ***	.0031	.0031	−.0002	.0012	.001	.0008
Blog entries	–	–	.0312	.0035 ***	.0181	.0057 ***	.0033	.0012 ***
Recommended	–	–	.7619	.0866 ***	.2976	.1379 **	.0789	.0254 ***
Self-started	–	–	−.1372	.0429 ***	−.0628	.0852	−.0019	−.0189
Number of in-between self pledges	–	–	.1482	.0207 ***	–	–	–	–
Number of self pledges after 75%	–	–	–	–	.4605	.0689 ***	.024	.0132 *
Years since launch of Startnext	−.0131	.0046 ***	.1485	.0215 ***	.1071	.0366***	−.0146	.0121
Category dummies	Yes		Yes		Yes		Yes	
N	2713		2254		635		945	

Marginal effects reported; robust standard errors.
* significance levels: = 10%.
** significance levels: = 5%.
*** significance levels: = 1%.
The specification in IIb includes severely under track projects; the one in IIc under track, slightly under track, on track, over track and rockets.

campaign's funding seems to be rather an indication of desperation than a useful tool to get the crowd going.

4.3. Potential drivers of late funding boosts

The fact that communication efforts (blog posts, videos) are determinants of project success might be indirectly linked with the late booms of severely under track projects, whose creators might have made an extra effort at reaching a larger audience. To check this line of argument we ran two additional regression specifications, restricted to severely under track projects (column IIb of Table 4) and to under track or closer (column IIc of Table 4). Results confirm that proxies for communication efforts (video count and blog updates) are not only correlated with project success for the entire dataset but also for the subset of severely under track projects; their effect is stronger than for projects closer to success. In order to capture the effect of late self pledges we have replaced the in-between self pledge variable with the number of self pledges after the 75% mark. For severely under track projects, the number of self pledges during the last quarter of funding is significant at the 5%-level, while for projects closer to their target at the 75% mark the estimated effect is positive but not significant. In terms of project categories, among severely under track projects music and movie projects have higher and technology projects lower success rates. Among projects closer to the target, only art projects are correlated with funding success (positively).

Our analysis so far suggests that communication activities and self funding play a role in making severely under track projects succeed eventually. However, our data are mute on the timing of the communication efforts. While we find a correlation between the extent of videos/blog updates and the success of severely under track projects, these activities may have taken place early on. Due to this lack of a time dimension of the communication data we decided to ask the parties closely involved in the funding processes about their experiences. We followed two roads: interviews with Startnext staff and a questionnaire allowing us to get insights directly from project creators.

First, we discussed the potential reasons behind the late boosts directly with Startnext. They generally advise project creators to prepare communication measures before the start of the funding in order to share news about the campaign (among existing contacts, in social networks, etc.) right when the funding duration starts. However, their experience is that not all projects are actively and consistently working the communication channels early on. Startnext suspects that late boosts take place when such projects start to share and communicate about their campaign.

Second, we conducted a questionnaire among project creators designed to identify their general approach to present their project and communicate about it, and the possible changes of strategy along the course of the funding campaign. We focused on severely under track projects with a funding target of more than € 5000 and a minimum of 50 pledges. This resulted in 40 projects, 15 failed, 25 succeeded to get funded.[14] We eyeballed their scatter plots in order to filter out unsuitable patterns (very low pledge activity after 50%, high extent of self pledges) which reduced the sample by 6. Valid email addresses could not be found for 9 projects. Thus, we sent out in total 25 questionnaires, 15 to successful and 10 to failed projects. We contacted project creators by email or web form with our invitation text linking to an online platform. We pledged to reward complete responses to the questionnaire with a € 20 gift voucher and received responses from 8 successful and 4 failed projects. See Appendix B for a translation of the original German questionnaire.

A complete summary of the questionnaire replies, grouped according to key project metrics (target amount, dynamic pattern before the 75% mark of the funding duration) and contrasting failed vs. successful projects within each group is given in Table 8, Appendix C. This allows us to compare the activities of projects that are relatively similar in terms of funding target and development, knowing that some managed to reach their target, while their ‘twins’ did not. Plots of funding over project time are also shown in Appendix C (one success and one failure of each group).

All successful projects stressed that continuous communication effort was needed over the whole campaign. Towards the end of the campaign, six out of eight projects intensified social media campaigns that were present from the start. Five out of eight started/intensified communication to their direct network by personally contacting friends, family and acquaintances, or mobilizing the company newsletter contacts. Two projects started/intensified communication on the Startnext website, initiating a video series and a blog, actively replying to all comments on the platform. Two projects added new reward levels

[14] In order to improve the sample balance with respect to failures/successes we softened the pledge minimum to 35 for the failures.

in mid-campaign, one of them following a forum comment wondering about such a reward level. The role of self pledges and angel investors is also present in questionnaire replies. One project, upon seeing no more pledges coming in for some time, directly asked family and friends for pledges, "*to get things going again*". Another project got to know after the campaign that a single user – unknown to the project creators up to that point – pledged around 25% of all funds in three distinct pledges just before the campaign's end (after having followed closely the performance of the project and to ensure success). The presentation of the project as well as the active and open communication was given as reasons by the user. A third project personally contacted friends and acquaintances towards the end of the campaign which led to several substantial pledges pushing the funding across the threshold. A fourth project self pledged six times between 80% of project time and right after it reached its target. The pledge boost driving the project to success seems to have started already before the first self pledge was made.

Failed projects in general report a carefully planned set of activities at the beginning. Three out of four projects, however, do not followed up nor intensified as the campaign proceeded. Project 2226 recounts that they participated at public events showing their prototype when the campaign started. They did not report further activities in the remaining campaign. They made eight self pledges between 60% and 95% of project time, however, without any apparent influence on the subsequent frequency of pledges. Project 386 answers that they contacted friends, acquaintances and existing clients about the project when the campaign started. They also posted in social media (Facebook, Twitter). They did not continue, let alone intensify, their communication efforts in the remainder of the campaign. They also told us they realized not being persistent with communicating about the project was a mistake. A follow-up project later that year succeeded. Project 1603 reports that they contacted journalists at the beginning of the campaign. Around the midpoint they started to post on Facebook and towards the end of the campaign they sent out emails to friends/acquaintances. Project 2248 recounts that they distributed a newsletter and a mailing to the press when the campaign started. Afterwards, they updated their Facebook and project web site.

Overall, the impression from the responses of projects that eventually succeeded is that they intensified their communication efforts on social media channels and/or managed to activate substantial support from their friends/family (or even big donors previously unknown to them). In contrast, most projects that eventually failed tell us that they did not step up communication efforts towards the end of the campaign.

4.4. Econometric analysis of herding and self pledges

Our analysis so far focused on descriptives and identified general patterns in the data. We now turn to an econometric model to shed more light on the relationships behind the funding dynamics. In order to analyze the effect of social influence we set up a panel consisting of all projects that made it to the funding phase. While we have the time stamp of each pledge to each project, a panel using an exact time variable would mostly contain zeroes (since at the very time stamp of one project other projects most likely did not receive pledges). Hence, we have to trade off time precision and tractability of the regression analysis. We decided to collapse project time into 100 units that we call ticks. Therefore, all pledges a project collects within one tick are summed up. Since funding targets differ across projects we normalize the pledged amount received. Thus, the funding ratio y is the cumulative pledged amount to a project at the end of one tick divided by the project's target amount. The increase of the funding ratio during one tick, Δy, is our dependent variable.

From our descriptive analysis we already know that pledges are distributed unevenly over project time. We observe a higher volume of pledges in the beginning and towards the end. We control for this by using dummies dividing project time in ten equally-long intervals. Thus, interval 1 represents the first 10% of a project's funding duration and interval 10 the last 10%. In the regressions, interval 6 serves as the baseline. In order to proxy the effect of social influence we use the increase of the funding ratio during the previous tick as our main explanatory variable. The idea of this approach is to capture funding increases triggered by users getting information about recent funding choices of others, independently of the current funding ratio of the project. We discuss an alternative, using the previous tick's funding ratio, later on. Since our previous analysis revealed substantial heterogeneity of funding dynamics, we interact our interval dummies with the lag of the funding ratio's increase. Thus, we test whether herding takes place in specific intervals of the funding period.

We use project fixed effects to take unobserved heterogeneity at the project level into account.[15] In

$$\Delta y_{\mathrm{it}} = \alpha + \beta_1 \cdot \Delta y_{i,t-1} + \beta_2 \cdot I_t + \beta_3 \cdot \Delta y_{i,t-1} \cdot I_t + \beta_4 \cdot K_{\mathrm{it}} + \nu_i + \epsilon_{\mathrm{it}}$$

the dependent variable Δy_{it} is the increase of project i's funding ratio in tick t, I_t is a vector of dummy variables controlling for the time interval, K_{it} is a vector of control variables, the project-specific error term is ν_i, the residual is ϵ_{it} and $t = 2, \ldots, 100$. The relatively high number of ticks has the advantage that it evades 'dynamic panel bias' (Nickell, 1981) which complicates the analysis of 'small T, large N' panels featuring a lag dependent variable (Roodman, 2006).

Table 5 shows the regression results in column 1. We observe positive level effects of early intervals (1–3) and late ones (7–10). The main effect of Δy_{it-1}, the lag of the increase of the funding ratio, is not significant. The interaction term of the first interval and Δy_{it-1} is positive and significant at the 1%-level. Moreover, the interaction terms between Δy_{it-1} and the seventh, eighth and last interval are also positive (significant at the 5%-level). It seems that there is no general herding. It is rather limited to the start of the funding period and towards its end. The specification in column 2 tests for the effect of self pledges. We include the number of a project's self pledges during the previous tick as a main term as well as interacted with the intervals. Results indicate no general effect of the extent of self funding.

These results generally establish an effect of social influence. An increase of the funding ratio in the previous tick is estimated to have an effect of up to 11% (during interval 1) on the increase in the current tick. We now dig a bit deeper looking at specific project types. Column 3 of Table 5 shows a separate regression for severely under track projects; column 4 considers all other projects. The categorization uses the data-driven approach described earlier at 75% of project time.[16]

The distribution of pledges over project time exhibits the familiar pattern for both severely under track projects and the rest. We observe high pledged amounts in the beginning/end, while in the middle of the funding duration the volumes tend to be lower. For both categories, positive cascades take place in interval 1 (significant at the 1%-level). They seem to be more pronounced for projects not severely under track (coefficient of 0.11) than for severely under track projects (0.073). In late intervals (8 to 10), the coefficients of severely under track projects are significant (at the 5/1/1%-levels), while the coefficients of the remaining projects are marginally significant (interval 7) at best. It seems that towards the end of the funding duration herding takes place only among severely under track projects. The estimates for the effect of a funding ratio increase in the previous tick on the funding ratio increase in the current tick range from 6.5% to 7.4%.

Moreover, we find a positive correlation between the funding increase and the number of self pledges in the previous tick for severely under track projects in the seventh interval. However, taking the main effect of the number of self pledges into account, the statistical significance is only marginal ($p = 0.08$). While we identified in-between

[15] Due to the normalization and collapsing of the data we cannot control for the day of week, month or year.

[16] Alternative specifications with smaller values for project time like 50%, 60% or 70% deliver qualitatively similar results as the ones reported.

Table 5
Determinants of the increase in pledges over time.

	1: Dynamics		2: Self funding		3: Severely under track		4: Others		5: Multicollinearity		6: Funding ratio		7: Goal proximity	
L.Funding ratio increase	0.0083	(0.009)	0.0070	(0.008)	−0.036***	(0.01)	0.014	(0.010)					−0.0016	(0.008)
Interval 1	0.0033***	(0.0004)	0.0034***	(0.0004)	0.0020***	(0.0001)	0.0058***	(0.0009)	0.0033***	(0.0004)	−0.00067	(0.0006)	0.0043***	(0.0004)
Interval 2	0.0012***	(0.0002)	0.0012***	(0.0002)	0.00085***	(0.0001)	0.0018***	(0.0005)	0.0012***	(0.0002)	−0.0018***	(0.0004)	0.0018***	(0.0003)
Interval 3	0.00051**	(0.0002)	0.00052**	(0.0002)	0.00033***	(0.00010)	0.00077	(0.0005)	0.00049**	(0.0002)	−0.00072**	(0.0003)	0.00085***	(0.0002)
Interval 4	0.00043	(0.0003)	0.00043	(0.0003)	0.00017*	(0.00009)	0.00080	(0.0008)	0.00041	(0.0003)	−0.00051*	(0.0003)	0.00050*	(0.0003)
Interval 5	0.000014	(0.0002)	0.000018	(0.0002)	0.000037	(0.00009)	−0.000024	(0.0005)	−0.0000065	(0.0002)	−0.00040	(0.0003)	0.000074	(0.0002)
Interval 7	0.00076***	(0.0003)	0.00078***	(0.0003)	−0.0000022	(0.00009)	0.0020***	(0.0006)	0.00075***	(0.0003)	0.0011***	(0.0003)	0.00088***	(0.0003)
Interval 8	0.0014***	(0.0003)	0.0014***	(0.0003)	0.00091***	(0.0002)	0.0021***	(0.0006)	0.0014***	(0.0002)	0.0022***	(0.0003)	0.0019***	(0.0003)
Interval 9	0.0035***	(0.0005)	0.0035***	(0.0005)	0.0036***	(0.0004)	0.0033***	(0.001)	0.0035***	(0.0005)	0.0043***	(0.0007)	0.0047***	(0.0005)
Interval 10	0.0099***	(0.0005)	0.0098***	(0.0005)	0.0094***	(0.0007)	0.010***	(0.0008)	0.0098***	(0.0005)	0.0096***	(0.0008)	0.013***	(0.0006)
L.Funding ratio increase × Interval 1	0.11***	(0.03)	0.12***	(0.03)	0.073***	(0.02)	0.11***	(0.03)	0.12***	(0.03)			0.11***	(0.03)
L.Funding ratio increase × Interval 2	0.015	(0.02)	0.016	(0.02)	0.020	(0.01)	0.014	(0.02)	0.023*	(0.01)			0.0078	(0.02)
L.Funding ratio increase × Interval 3	−0.0025	(0.01)	−0.00073	(0.01)	0.029*	(0.02)	−0.0029	(0.01)	0.0063	(0.008)			−0.011	(0.01)
L.Funding ratio increase × Interval 4	−0.015	(0.010)	−0.014	(0.010)	0.024	(0.02)	−0.020*	(0.01)	−0.0069	(0.004)			−0.0083	(0.008)
L.Funding ratio increase × Interval 5	−0.0063	(0.01)	−0.0057	(0.01)	0.019	(0.02)	−0.0067	(0.01)	0.0013	(0.008)			−0.012	(0.01)
L.Funding ratio increase × Interval 7	0.038**	(0.02)	0.040**	(0.02)	−0.020	(0.02)	0.035*	(0.02)	0.047***	(0.02)			0.046**	(0.02)
L.Funding ratio increase × Interval 8	0.030**	(0.01)	0.031**	(0.01)	0.066**	(0.03)	0.026	(0.02)	0.038***	(0.01)			0.035***	(0.01)
L.Funding ratio increase × Interval 9	0.11	(0.08)	0.12	(0.08)	0.074***	(0.02)	0.17	(0.1)	0.12	(0.08)			0.13	(0.08)
L.Funding ratio increase × Interval 10	0.025**	(0.01)	0.023**	(0.01)	0.065***	(0.02)	0.014	(0.02)	0.030***	(0.008)			0.043***	(0.01)
L.Self pledges			0.0026	(0.003)	−0.0022*	(0.001)	0.0043	(0.004)	0.0029	(0.003)	0.0035	(0.003)	0.0024	(0.004)
Interval 1 × L.Self pledges			−0.0031	(0.004)	0.0024*	(0.001)	−0.0043	(0.006)	−0.0034	(0.004)	0.00026	(0.004)	−0.0024	(0.004)
Interval 2 × L.Self pledges			0.00039	(0.005)	0.0044**	(0.002)	−0.00064	(0.008)	0.000090	(0.005)	−0.00058	(0.005)	0.00040	(0.005)
Interval 3 × L.Self pledges			−0.0039	(0.004)	0.0051	(0.005)	−0.0071	(0.004)	−0.0042	(0.004)	−0.0044	(0.004)	−0.0033	(0.004)
Interval 4 × L.Self pledges			−0.00096	(0.004)	0.00016	(0.002)	−0.0017	(0.005)	−0.0013	(0.004)	−0.0022	(0.004)	−0.00097	(0.004)
Interval 5 × L.Self pledges			−0.0013	(0.004)	0.00098	(0.003)	−0.0024	(0.005)	−0.0016	(0.004)	−0.0016	(0.004)	−0.0013	(0.004)
Interval 7 × L.Self pledges			−0.0047	(0.004)	0.0053***	(0.002)	−0.0084*	(0.005)	−0.0050	(0.004)	−0.0033	(0.004)	−0.0052	(0.004)
Interval 8 × L.Self pledges			−0.00045	(0.005)	0.0011	(0.004)	−0.00067	(0.007)	−0.00075	(0.005)	0.0017	(0.005)	−0.00081	(0.005)
Interval 9 × L.Self pledges			−0.0084	(0.009)	0.011	(0.01)	−0.017	(0.01)	−0.0087	(0.009)	0.0035	(0.005)	−0.010	(0.009)
Interval 10 × L.Self pledges			0.0018	(0.005)	0.013*	(0.007)	−0.0032	(0.005)	0.0015	(0.005)	0.0038	(0.004)	0.0014	(0.005)
L.Funding ratio											−0.016***	(0.003)		
L.Funding ratio × Interval 1											0.023***	(0.004)		
L.Funding ratio × Interval 2											0.0034*	(0.002)		
L.Funding ratio × Interval 3											−0.0031**	(0.001)		
L.Funding ratio × Interval 4											−0.0012	(0.001)		
L.Funding ratio × Interval 5											−0.00060	(0.001)		
L.Funding ratio × Interval 7											0.0015**	(0.0007)		
L.Funding ratio × Interval 8											0.0019**	(0.0009)		
L.Funding ratio × Interval 9											0.0054***	(0.001)		
L.Funding ratio × Interval 10											0.0082***	(0.001)		
L.% Goal funded 20–40													0.0019***	(0.0005)
L.% Goal funded 40–60													0.0049***	(0.0006)
L.% Goal funded 60–80													0.0069***	(0.0008)
L.% Goal funded 80–100													0.0029***	(0.0010)
L.% Goal funded 100+													−0.013***	(0.0009)
Constant	0.0037***	(0.0002)	0.0037***	(0.0002)	0.00091***	(0.0001)	0.0074***	(0.0004)	0.0037***	(0.0002)	0.0086***	(0.0009)	0.0026***	(0.0003)
Observations	223146		223146		129591		93555		223146		223146		223146	
R^2	0.014		0.014		0.014		0.016		0.014		0.014		0.024	

Fixed effects panel regressions with 100 ticks as the normalized time variable; robust standard errors in parentheses; the dependent variable is the funding ratio increase in one tick; L.x means the first lag of regressor x.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

self pledges as a positive determinant of project success, our data do not support that self pledges affect subsequent funding, that is, trigger herding behavior. Changing/extending the sub-sample to under track projects does not lead to different results.

4.5. Robustness checks

In the following we discuss the robustness of our results. We first test for multicollinearity in our regression model. The variance inflation factor of the lagged funding ratio increase is above the conventional cutoff of 10, while all others are below. In order to test whether this affects our results, we drop the main term of the lagged funding ratio increase. The results of the adjusted regression are in column 5 of Table 5. The effect of momentum appears slightly stronger early on (higher interaction coefficient in interval 1 and a marginally significant interaction coefficient in interval 2) and as well towards the end of the funding duration (1% – levels of significance in intervals 7, 8 and 10). Our analysis uses the funding ratio increase in the previous tick to measure the effect of social influence on project funding. Also the actual value of the funding ratio appears to be a reasonable measure as a project's current funding level and its funding target are shown on its page. This approach would focus on the cumulative funding amount of a project which could be regarded as an expression of previous pledgers' collective evaluations of the project. Column 6 of Table 5 presents results for the corresponding regression. Using the funding ratio as regressor instead of the funding ratio increase delivers very similar results. The effect of momentum seems stronger towards the end of the funding duration (interaction coefficients in intervals 7–10 significant at least at the 5%-level). In interval 1 the interaction coefficient is highly significant but there is no level effect.

4.6. Discussion of results

Our regression results provide two insights about the dynamics of reward-based crowdfunding. Information cascades do not only take place at the start of campaigns but also later, especially during the last quarter of funding. Thus, the notion of path dependence holds only partially: a strong start is almost a guarantee for success, yet a slow start does not rule out that a project gets funded eventually. Moreover, we find only partial evidence in line with a goal proximity effect as proposed by Kuppuswamy and Bayus (2017). While our data support a correlation between added pledgers and a project's proximity to its funding goal (their specification), we do not find an effect of goal proximity using the increase of funding as dependent variable and its lag (see column 7, Table 5) or the lag of cumulative funding as an explanatory variable. It seems that more pledges are made the closer a project gets to its funding target, but the total amount pledged to a project does not increase.

We conclude the results section with a discussion of the limitations of our approach. Our quantitative and qualitative analysis indicates that communication efforts of severely under track projects lead to increases of the pledged amount. Communication activities may have attracted additional pledges which, in turn, triggered an information cascade. The behavioral pattern we find in our data is consistent with such observational learning. Alternatively, all new pledges may have been caused directly by communication. This seems unlikely given the short amount of time that passes between sending and receiving information in social media networks. The 'half-life' of a tweet is 24 min and the one for a Facebook post is 90 min according to Wiselytics (2014). Thus, it seems probable that pledges directly resulting from a post/Tweet would tend to be made on the same day.

However, we cannot rule out that instead of observational learning another social influence channel, namely, word of mouth, is to be attributed for the increase of pledges following a communication trigger. While observational learning means that a cascade develops within the crowdfunding platform (due to observing others' actions), word of mouth implies that information about the project spreads within another platform, a social media network (due to reading others' endorsements of the project). Some exposed to the endorsements may turn into pledgers. Thus, both underlying processes would diffuse in similar fashion and both would result in the behavioral pattern we observe. See Ellison and Fudenberg (1995) for a theoretical approach to model social learning via word of mouth. For the scope of our study, it is only of interest whether social learning occurs, not on which platform and via which channel (observations and/or opinions/endorsements). Of course, the question where/how social learning takes place in crowdfunding environments remains as a topic for future research. See Chen et al. (2011) for an empirical analysis that disentangles between the two processes in the context of product purchases. See Kaminski et al. (2018) for a study on the interplay between two forms of electronic word of mouth, online forum interactions (on Kickstarter) and social media activity (on Facebook).

5. Conclusion

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 allows us to investigate the dynamics of pledges, explore the motivations of pledgers and assess the impact of self funding.

Project funding dynamics exhibit early cascades of positive reinforcement known from previous research (van de Rijt et al., 2014), however, such pledge boosts also happen relatively late during the funding phase. Thus, project success is only partially path-dependent. Having a strong start is almost universally leading to success, consistent with the findings of Colombo et al. (2015), but the converse is not true: a slow start can still lead to success in a relevant percentage of cases. About 40% of projects that lag behind by 30 or more percentage points with respect to the average project still manage to reach the funding threshold, thanks to the attraction of large pledges in the last quarter of project life. An econometric analysis that fully exploits our rich pledge-level dataset supports this key finding of late stage herding.

Our analysis of funding dynamics shows that projects can get boosted to eventual success at virtually any point of time. The crowdfunding literature has already identified communication to be a key driver of success. Studies have focused on quality indicators of projects' communication (Mollick, 2014), dialogue between fundraisers and pledgers (Beaulieu and Sarker, 2013; Kromidha and Robson, 2016; Wang et al., 2018), and project descriptions' language (Herzenstein et al., 2011b; Frydrych et al., 2016; Gafni et al., 2017). Our paper goes a step further, showing that such communication efforts are a key element driving the late surges. While our quantitative data do not allow us to connect the increase in pledges to specific communication efforts, results from our qualitative analysis (interviews with Startnext staff, questionnaire responses from severely under track projects) directly confirm this conjecture (see Borst et al., 2017, for related evidence of social media usage (Twitter, facebook)). It seems that successful communication matters, irrespective of those efforts being made early or late in a project's life.

These results tie in with related findings by Stanko and Henard (2017) with respect to the relationship between crowdfunding and innovation. It seems that an engaging dialogue between project and its community during the campaign can be beneficial in at least three dimensions. It tends to improve the project's chances to get funded in the first place, the quality of the future product (via 'open search') and the diffusion of the product (via activating 'earliest adopters'). As crowdfunding is well-suited to encourage discourse (in comparison to traditional entrepreneurial financiers), it may have a competitive edge beneficial for innovation. Moreover, the benefits of discourse with the crowd appear to go beyond the current product/service as evidenced by research on serial crowdfunders (Butticè et al., 2017; Skirnevskiy et al., 2017).

Another interpretation of the observed late surges of severely under track projects points to self funding. The disproportionally large pledges that tend to drive those boosts might originate from project creators themselves. Since Startnext allows self pledges, we are able to directly identify them and study their impact on project success and dynamics. This is unique in the crowdfunding literature and in contrast to platforms like Kickstarter or Indiegogo who prohibit self pledges and sanction indirect self funding attempts. Formal self pledge bans are easily circumvented (KickstarterForum, 2014; Dresner, 2014), and it is hence likely that self funding takes place in the dark. Our analysis provides a measure of the extent of self funding and assesses its impact on the funding process that would not be possible in environments where self funding is not transparent. Furthermore, the patterns and distinctive characteristics of self pledges that we uncover could be helpful to detect self pledges at sites that do not allow them.

We find that project creators self pledge strategically, with three main goals in mind: starting off a campaign, trying to re-create interest in it after some inactivity, and secure funding by providing the pivotal pledge that pushes the project over the threshold. Even if overall just 1.6% of pledges are self-funded, a full third of project creators self pledges at least once, and one project in ten is either started or pushed over the threshold by a self pledge. We find no compelling evidence of an indirect effect of self pledges. In fact, self-started campaigns are significantly less likely to reach the funding target. Presumably, project quality is a bigger determinant than the attempt to self-start funding. Moreover, our results do not indicate that self pledges trigger subsequent herding behavior.

We further find no connection between self pledges and late surges at (severely) under track projects. These are mostly driven by external funders who make large pledges, rather than insiders tugging the project forward. Our results indicate that external individuals ('angels in the crowd') can play an important part in the funding process, similar to what happens in the context of crowd-investing.[17]

Overall, our analysis reveals that there are attempts of phishing. But is the crowd actually phooled by the self funding (Akerlof and Shiller, 2015)? We have established that self pledges do not seem to have a positive impact on subsequent funding, yet persistent self funding (6% of all projects self pledge more than a quarter of their campaign target) leads to eventual funding success. It is not clear, though, whether these interventions necessarily bias funding decisions in a negative way. Sometimes projects worthy of funding require information cascades to tap sufficient support from the crowd (Parker, 2014). Either way, the practice of self funding seems to contradict the concept of 'open innovation' that is generally understood to be of high importance for the success of startups. Giudici et al. (2018), for instance, stress the role of inbound open innovation – attracting innovative funders that can contribute to project development – in the case of crowdfunding. In contrast to the open exchange between creator and crowd, self funding appears to be a remnant of the previous, closed approach to innovation. Self pledges, if discovered by the crowd and perceived as an attempt to manipulate the funding process, may also be detrimental to the relationship between creator and crowd. André et al. (2017) argue that trust can be an important ingredient for the success of a campaign as pledges are to a substantial extent based on reciprocal behavior. Self funding would undermine such trust. An analysis of ultimate project success (does a project deliver on its promise or not?) of self funded projects would be able to shed light on the longer-term consequences of self pledges. This remains as a future avenue of research since our data do not allow us – beyond a simple analysis of subsequent projects by the same project creator – to assess the actual delivery rate of projects.

[17] Vismara (2016) finds that early investors with public profiles play an influential role as they trigger information cascades.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.respol.2018.04.020.

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