Network Effects in Crowdfunding

Paul Belleflamme, Thomas Lambert, and Armin Schwienbacher*

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Abstract

We study the various network effects that are at work on crowdfunding platforms. From a theoretical perspective, we distinguish between network effects that relate to participation or to usage decisions. We use novel entrepreneur-backer data to identify their relative importance on project funding dynamics. We empirically show that backers decide on their usage of the platform based on intra-project activity – as documented by prior work – but also on inter-project activity. In a difference-in-differences research design, we estimate that inter-project network effects account for 2-3% in the increase of contributions that projects generate on a daily basis. Then we find that participation decisions create a positive feedback loop fueling the growth of the platform and explaining how positive inter-project network effects can arise. Our results represent the first attempt in the literature to unbundle the web of network effects on project funding dynamics and suggest that many existing results in the crowdfunding literature are driven by network effects.

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* Paul Belleflamme is with CORE, Université catholique de Louvain (Voie du Roman Pays, 34, 1348 Louvain-la-Neuve, Belgium, paul.belleflamme@uclouvain.be). Thomas Lambert is with Rotterdam School of Management, Erasmus University (PO Box 1738, 3000DR Rotterdam, The Netherlands, t.lambert@rsm.nl). Armin Schwienbacher is with SKEMA Business School – Université Côte d'Azur (Avenue Willy Brandt, 59777 Euralille, France, armin.schwienbacher@skema.edu). We are very grateful to Ulule for providing data, and especially to Romain Burgot for being so generous with his time in answering queries. We also thank seminar participants in Louvain-la-Neuve, Montpellier, Nancy, Paris, and Rotterdam for useful comments. Part of this research was conducted when Paul Belleflamme was with Aix-Marseille School of Economics and Kedge Business School. Any remaining errors are our own. We acknowledge financial support from the French Ministry DEPS/Labex ICCA (research grant on "Crowdfunding in Arts, Culture, and the Media").

1. Introduction

The advances in FinTech and sharing economy are largely driven by the economic value of network effects. The decisions that users make on digital platforms are highly interdependent, insofar as their decisions jointly condition the value they will obtain from interacting on the platform.[1] This amounts to say that users care about the usage and participation decisions of other users. Although network effects are at the heart of the rise of digital platforms such as Ethereum, LendingClub, or PayPal, little systematic evidence exists on their incidence.

In this paper we attempt to fill this gap using a crowdfunding platform (referred to hereafter as CFP) as a laboratory for our analysis. CFPs facilitate the interaction between entrepreneurs in need for funding and backers interested in financing projects. Therefore, the success of CFPs strongly depends on how network effects emerge and are managed. Against this background, we pursue two goals. First, we map the web of network effects at work on CFPs. We distinguish between two sources of network effects: increased participation (by additional backers or entrepreneurs who decide to join the platform) and increased usage (mainly by existing backers who decide on which project to contribute). Second, we show evidence identifying the presence of these network effects in crowdfunding and assess their relative intensity. Specifically, we proceed by focusing on backers' contributions on the universe of projects listed on Ulule, one of the leading reward-based CFPs in Europe. Between 2010 and 2016 (our sample period), Ulule attracted more than 1.3 million of backers on about 24 thousands entrepreneurial projects.[2]

Our data reveal clear evidence of the prevalence of network effects in crowdfunding. We are interested primarily in network effects that arise *within the group of backers*. The basic question

[1] Communication devices offer a typical example of network effects: the more subscribers there are, the more valuable the device is for each of them. However, the interdependence of users' decisions gives rise to coordination problems. For instance, even if users agree that they would benefit if they were all adopting the same communication device, none of them may be keen enough to make the decision individually and face the risk of not being followed. Intermediaries may then step forward to solve such coordination problems by actively bringing users together. Even if intermediaries of that sort have been around for ages (e.g., Fisman and Sullivan, 2016, draw the parallel between modern platforms and the Champagne Fairs in 12th century France), the fast penetration of the Internet and digital technologies over the last two decades has allowed digital platforms to manage network effects on unprecedented scale and scope. See Rohlfs (1974) and Katz and Shapiro (1985) for seminal analyses of network effects; see Belleflamme and Peitz (2018) for a recent survey of the literature on network effects and digital platforms.

[2] Reward-based CFPs appear to be a superior setting than equity-based CFPs to identify network effects since the number of campaigns running simultaneously is significantly larger in the former. The reasons are that reward-based crowdfunding projects are simpler to set up and the screening process is lighter. Furthermore, we have replicated all our analyses using data from another large CFP based in France, KissKissBankBank, and the results are similar. These results can be obtained upon request.

here is how do backers impact one another through the decisions they make. In this regard, we find that current backers' contributions to a particular project are positively influenced by previous backers' contributions to that project. We confirm thereby the existence of positive 'intra-project network effects', which have already been documented in the literature. We also show an entirely novel result, namely the existence of positive '*inter*-project network effects': current contributions to some project increase with past contributions to *other* contemporaneous projects on the CFP. To establish these results, we estimate a dynamic panel model using the standard within estimator as well as a moment-based estimator with better asymptotic properties. Our central estimates using this strategy indicate that the number of contributions generated by a project on a daily basis is approximately 2% higher following a 10% increase in the number of contributions within the same project (i.e., positive intra-project network effects) and approximately 0.5% higher following a 10% increase in the number of contributions in the other projects on a daily basis (i.e., positive inter-project network effects).

In order to establish more precisely the causal impact of inter-project network effects, we utilize 'fast starters', which are projects having generated an unexpectedly high number of pledges during the very first day of their campaign. In a difference-in-differences research design, we examine inter-project network effects on project funding outcomes surrounding fast starters' first campaign day. Our difference-in-differences estimates indicate that inter-project network effects account for 2-3% increase in the number of contributions that a particular project obtains on a daily basis. We also find that inter-project network effects produced by fast starters are more pronounced on projects belonging to the same category than the fast starter. In the latter case, they account for 7.7% increase in the number of contributions on a daily basis.

Our empirical setting also allows us to get to grips with network effects that arise *across the groups of backers and entrepreneurs*. Here, the question is how do backers value the participation of additional entrepreneurs and vice versa. We first observe that the combined impact of these two 'cross-group network effects' is positive: participation on the platform generates a positive feedback loop (more entrepreneurs attract more backers, who in turn attract more entrepreneurs). This fuels the growth of the platform and explains how positive inter-project network effects can arise.[3] In economic terms, we document a compound daily growth rate of backers' contributions on the CFP of 0.25% (or of 172% on an annual basis).

Further analyses allow us to identify the positive cross-group network effect that entrepreneurs exert on backers. Using backer-level data, we examine whether backers' propensity to pledge again on the CFP relates to the size of the group of entrepreneurs. These tests aim at disentangling the value that backers extract from the participation of additional entrepreneurs. Our estimates show that the probability that backers will contribute again increases by 42.1% as the size of the group of entrepreneurs increases by a one standard deviation. In addition, our backer-level data allow us to disentangle the value that backers generate from the participation of other backers, that is, the intensity of 'within-group network effects'. Interestingly, we find that within-group network effects go in the opposite direction. Our estimates indicate that backers' probability to contribute again drops by 49.3% for a one standard deviation increase in the size of the group of backers. In short, cross-group (from entrepreneurs to backers) network effects increase the participation of backers and so the size of the CFP, whereas within-group (from backers to backers) network effects tend to rein in the size of the CFP.

Our findings have significant implications for CFP management and competition. From a *managerial perspective*, our analysis suggests that the success of a CFP depends not only on the quality and quantity of the projects that are proposed to potential backers, but also on the way these projects are mixed. Because synergies exist between projects (as evidenced by the presence of positive inter-project network effects), CFPs can increase total contributions by choosing the right mix of projects. In this regard, the detailed analysis that we perform at the level of project categories provides CFP managers with useful indications. On Ulule for instance, we show that the 'Music and Art & Photos' category is the one that generates the largest synergies; the platform may then want to give more visibility to projects in this category, as they are more conducive to stimulate platform growth. Another important lesson that CFP managers can draw from our work is that recurrent backers behave quite differently from new backers. In particular, we show that projects having a higher fraction of recurrent backers appear to generate more contributions, suggesting that retaining existing backers may yield larger returns than acquiring new backers.

[3] If projects were competing for a fixed volume of contributions, they would necessarily exert a negative impact on one another; that is, inter-project network effects would be negative.

From a *competition point of view*, our results suggest that reward-based crowdfunding is a 'winner-takes-all' type of market: the several sources of positive network effects that we identify create positive feedback loops, which tend to make strong CFPs stronger and weak CFPs weaker. Hence, a CFP that manages to grow faster than its rivals may acquire a self-sustaining competitive advantage, leading eventually to market domination. This also means that the only survival prospects for smaller CFPs are to be found in specialization (finding the right niche) or in consolidation (merging with other CFPs). These implications for CFP competition thus resonate with the heated debate about the dominance of big tech platforms (Amazon, Facebook, Google) and the way network effects serve as an entry barrier.[4]

This paper relates to different strands of the literature. We briefly describe these connections here (we perform a more systematic review in the next section). First, this paper adds to the literature on reward-based crowdfunding, which has been mushrooming over the past years.[5] Let us mention two recent papers that are particularly relevant for our purpose. Kuppuswamy and Bayus (2017a) study the dynamics of project contributions over time, that is, what we call 'intra-project network effects'. They find that project support does not increase linearly over the funding cycle but typically accelerates as the target goal is in view. Thies, Wessel, and Benlian (2018) explore the network effects that stem from increased participation on a CFP. Their findings suggest that network effects across groups are asymmetric: entrepreneurs exert much stronger effects on backers than backers do on entrepreneurs. We note that these papers remain silent about 'inter-project network effects'. Furthermore, our novel entrepreneur-backer data allow us to examine participation decisions at the individual backer level, unlike Thies et al. (2018) who employ data aggregated at the category level. Second, the literature on other forms of crowdfunding is also relevant for our work. In particular, the empirical research on marketplace lending reports information cascades and herding behavior among lenders (see, e.g., Zhang and Liu, 2012), which are akin to the intra-project network effects that we document here. Finally, this paper also contributes to broadening the scope of the body of work that aims at estimating empirically the strength of network effects on multisided platforms (see, e.g., Chu and

[4] See, e.g., 'How to tame the tech titans', *The Economist*, January 18, 2018; see Rolnik (2018) for a recent academic discussion.

[5] A partial list of the literature on reward-based crowdfunding (theory and empirics) includes: Belleflamme, Lambert, and Schwienbacher (2014), Mollick (2014), Burtch, Ghose, and Wattal (2015), Cumming, Leboeuf, and Schwienbacher (2015), Mollick and Nanda (2016), Kuppuswamy and Bayus (2017b), Strausz (2017), Xu (2017), Chemla and Tinn (2018), Cong and Xiao (2018), Viotto da Cruz (2018).

Manchanda, 2016, on consumer-to-consumer platforms). What we add to the existing studies is twofold. First, we draw a clear distinction between the network effects that stem from participation and from usage decisions.[6] Second, we highlight the importance of the time dimension (of crowdfunding campaigns) for network effects to materialize.

The rest of the paper runs as follows. Section 2 proposes a mapping of the network effects that are at work on CFPs and then derives testable hypotheses. Section 3 introduces Ulule and describes the data. Section 4 presents our empirical results. Section 5 concludes.

2. Theoretical Framework and Hypotheses

2.1. Mapping network effects in crowdfunding

A product or a service exhibits network effects when the benefits that users derive depend on the participation and usage decisions of other users. These interdependent users form what is loosely called a 'network' (Belleflamme and Peitz, 2018). Entrepreneurs and backers form such a network when they engage into crowdfunding on a CFP. As users care about both the size and the composition of the network, crowdfunding generates a dense web of network effects, which CFPs try to manage so as to create value for the two groups of users (and for themselves if they are profit-oriented). In this respect, CFPs belong to the category of two-sided platforms, which enable the interaction between two 'sides' (here, entrepreneurs and backers) whose needs require coordination.

We distinguish network effects according to whether they are related to participation or to usage decisions.[7] One can see these two types of decisions as sequential: users first decide whether or not to use the services of a platform (participation) and then, they may still have to decide the frequency and/or intensity with which they use these services (usage). This distinction proves particularly relevant for crowdfunding, as the benefits that potentially accrue for entrepreneurs and backers depend not only on their simultaneous participation on a CFP, but also on their

[6] Therefore, our paper also relates to Li and Mann (2018), who focus on Initial Coin Offerings (ICOs). The authors theoretically present ICOs as a new mechanism to overcome coordination problems associated with the strategic participation/usage decisions of platform users.
[7] This distinction is inspired by Rochet and Tirole (2006), who distinguish between participation (in their words, 'membership') charges, which "condition the end-users' presence on the platform", and usage charges, which "impact the two sides' willingness to trade once on the platform".

repeated interaction over the duration of the funding campaigns. In particular, the combined usage of the platform by backers is crucial both for entrepreneurs (to get their projects funded) and backers (to receive their compensation).[8]

Arguably, the relative weight of these participation/usage decisions is not the same on the two sides of the platform. For entrepreneurs, participation decisions seem the most important: the bulk of their energy goes into the preparation of the funding campaign (once the campaign is under way, there is not much that they can do to change its course). The reverse applies to backers: once they have decided to participate to a CFP (which does not require much effort), they still have a range of complex usage decisions to make: they have to decide which project(s) to back, at which stage(s) of the campaign to make a contribution, how large a contribution to make, whether to communicate with friends about their decisions, etc. In many respects, these decisions are influenced by similar decisions taken by other backers. This interdependence between the backers' usage decisions generates specific types of network effects within the group of backers. These effects are dynamic by nature, as they play out for the whole duration of crowdfunding campaigns. We can thus also distinguish between network effects related to usage arising from the contributions to a single project or to different projects. To this end, we coin the terms '*intra*-project network effects' and '*inter*-project network effects'.

Last, our distinction between network effects related to participation and to usage thus implies different thought experiments. For network effects related to participation, we evaluate the impact of an increased presence (of entrepreneurs or of backers) on the platform, meaning that we examine the effect of a marginal increase in the *number* of entrepreneurs or of backers. In contrast, for network effects related to usage, we are interested in the behavior of backers once they are on the CFP. Here, we thus look at the effect of a marginal increase in the *contributions* pledged by backers.

In what follows, we first outline the network effects related to usage by distinguishing intra-project network effects from inter-project network effects. Then we consider network effects related to participation. We close this section by deriving testable hypotheses.

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[8] Arguably, the distinction between participation and usage is much less relevant for two-sided platforms on which the interaction between users of the two groups delivers an immediate value for them (think, e.g., of the renting of a house via Airbnb, or the use of an app on a smartphone).

2.2. Network effects related to usage

2.2.1. Intra-project network effects

Intra-project network effects are network effects that take place *within a particular project*. The crowdfunding literature has already documented this type of network effects on the funding dynamics for a particular project. The two main questions are: (1) Do past contributions influence current ones? (2) How does the cumulative distribution of contributions evolve during the campaign?

We can safely conjecture that the answer to the first question is yes. Because backers have limited information about the match value of the proposed projects and the trustworthiness of the entrepreneurs, they are likely to try and infer information from the choices made by previous backers. That is, past contributions do influence current ones, thereby generating intra-project network effects. However, the sign of these network effects is a priori ambiguous. To see this, consider a project that has already received a lot of support. A first reaction of prospective backers may be to infer that this project is of high quality and, consequently, to support it as well. A *herding behavior* of this sort (based on an information cascade) gives rise to positive intra-project network effects, as past backers attract new backers for a given project. In general, herding can be rational (i.e., due to observational learning and Bayesian updating)[9] or irrational (i.e., due to passive mimicking). Zhang and Liu (2012) provide evidence of herding (both rational and irrational) on the decisions of lenders on a marketplace lending platform. Another reaction may be backers' eagerness to contribute to a project as it approaches to its funding goal, that is, when they think that their impact is then the largest. This *goal-gradient effect* provides another source of positive intra-project network effects (Kuppuswamy and Bayus, 2017b).[10] In contrast, self-interested backers tend to rely on other backers to complete the funding (as they can fairly assume that further backers will be attracted by this already popular project). This *free-riding behavior* generates then a negative intra-project network effect. From 577 Kickstarter

[9] See Banerjee (1992), or Bikhchandani, Hirshleifer, and Welch (1992).

[10] This means that prospective backers may be in a position to be pivotal, that is, to provide the necessary financing for the project to reach its funding goal. Whether prospective backers decide to be pivotal or not depends on their behavioral profile. Altruistic motivations are invoked by Dai and Zhang (2018), who show that backers "are nearly three times as likely to fund a project right before it meets its funding goal as they are right after" (they use a dataset of 26,516 projects collected at 30-minute resolution from Kickstarter). Zvilichovsky, Danziger, and Steinhart (2018) study a related, but distinct, motivation for backers to feel pivotal; according to their experimental results, backers "are motivated to make the product happen more than they are motivated to help the entrepreneurs secure the campaign financing target."

projects, Li and Duan (2014) find the presence of the latter effect, alongside signs of herding behavior.

We can now turn to the second question of interest, namely how the cumulative distribution of contributions evolve during a campaign. Our previous analysis only provides us with partial answers, as the various effects that we outlined not only go in opposite directions, but also suppose that the project has already received a lot of support. So, the basic conundrum is how to attract contributions in the first place. Mollick (2014) finds that participation of the entrepreneur's personal network during the first days of the campaign is crucial in generating a momentum. Once an initial mass of contributions has been collected, intra-project network effects can start rolling off. We can conjecture that herding will drive contributions to grow steadily at first but, as the funding goal approaches, the dynamics will either accelerate or slow down according to whether it is the goal-gradient or the free-riding effect that dominates. Kuppuswamy and Bayus (2017a) suggest that the former effect dominates, leading to a distribution of contributions that is inverse U-shaped, with a maximum reached at the funding goal.[11]

2.2.2. Inter-project network effects

The different theoretical approaches reviewed above are useful to understand why network effects arise within a given project, but do not explain effects that may arise *across projects*. A quick extrapolation of our previous analysis would lead us to conclude that if intra-project network effects are positive, then inter-project network effects must be negative: if past contributions to a given project stimulate future contributions to this project, then they also discourage contributions to other projects.

However, this is unlikely to be the case as this reasoning relies on the flawed assumption that the set of backers and their willingness to contribute are fixed. In other words, the game would be zero-sum, making competition among projects extremely fierce. The volume of contributions on

[11] Hornuf and Schwienbacher (2018) show that in equity crowdfunding, the dynamics depends on how securities are allocated to backers: a concentration of contributions at the end of a campaign is much more likely to occur when securities are allocated in form of an auction instead of on a first-come-first-served basis. This finding is consistent with the fact that in equity crowdfunding the number of securities is limited (creating a risk of not being able to participate in the campaign for anyone who waits too long), while in reward-based crowdfunding campaign typically take all backers, regardless when they contribute. Wei and Lin (2017) find that for marketplace lending the two mechanisms also affect the quality of projects being proposed.

CFPs has been in continuous expansion over the last years and this trend shows no sign of decline, which suggests that crowdfunding is—and should remain for the years to come—a positive-sum game.

As a result, positive inter-project and intra-project network effects may well coexist, a hypothesis that (to the best of our knowledge) has not been properly tested so far. As we just hinted, a theoretical explanation for the existence of positive inter-projects network effects is the expansion of the total contributions on a given CFP, typically because new backers are attracted to the CFP. To understand why new backers would join the CFP, we need to examine network effects that relate to participation.

Before doing so, let us note that the magnitude and direction of the effects identified so far may vary across backers according to their familiarity with a given CFP. There are indeed reasons to believe that, compared to new backers, *recurrent* backers behave differently, and with different consequences. What makes recurrent backers different is the experience that they have accumulated on the CFP: they have learned how to use the platform, how to select and assess projects, how to follow campaigns, etc. Compared to new backers, recurrent backers are thus likely to make more informed choices and to be less influenced by the decisions of other backers. By the same token, their past decisions are also likely to exert a larger influence on current backers. In line with the herding story presented above, one can indeed argue that more information can be inferred from observing the behavior of more experienced decision-makers.[12] In our terminology, this means that recurrent backers should exert stronger intra-project network effects than new backers. At the same time, recurrent backers are potentially an important source of inter-project network effects, as they can decide to back sequentially different projects (either in the same or in different categories).

2.3. Network effects related to participation

Although users may base their decision to participate to a CFP on intrinsic motivations, they mostly rely on the observation of (or their expectations about) other users' decisions. Like many two-sided platforms, a CFP becomes more attractive for the users in one group as participation increases (or is expected to increase) in the other group. One talks here of *cross-group network*

[12] This explains why CFPs often find it profitable to allow backers to make their profile public. From equity offerings on Crowdcube (an equity-based CFP), Vismara (2016) shows that investors with a public profile (who are typically more experienced) increase the appeal of listings among early investors, who in turn attract late investors.

effects: the extent of participation in one group (entrepreneurs or backers) affects the benefits accruing to the participants in the other group. In general, one expects that such network effects are positive (Belleflamme, Omrani, and Peitz, 2015). The presence of more backers makes the platform more attractive to entrepreneurs, since it increases the probability of having their project funded and, sometimes, their ability to test the potential demand for their product. Similarly, backers will appreciate the fact that the platform has more entrepreneurs (thus, more projects posted), since it increases their chances of funding a project of their liking, and of receiving the most suitable reward.[13]

Another form of network effects stemming from participation decisions are *within-group network effects:* the participation decision by one user in a particular group not only affects participants in the other group, but also participants in this user's own group. For instance, the participation of an additional entrepreneur affects the value for other entrepreneurs using the platform. The same holds for backers. The impact of these network effects is a priori ambiguous (Belleflamme et al., 2015). Within the group of entrepreneurs, on the one hand, more entrepreneurs lead to greater competition for available funds, leading to negative network effects within the group of entrepreneurs. On the other hand, the effect may also be positive as the presence of more entrepreneurs can generate scale economies for the platform, or increase exchanges of best practices, or lead the platform to provide entrepreneurs with a better quality of service. The overall effect of these opposing forces is unclear and is thus an empirical question.[14]

Conflicting effects may also arise within the group of backers. A positive effect arises due to the increased availability of funds overall, which makes it more likely that more projects are funded; this benefits all backers, as they all want their preferred project to be funded, which becomes more likely as more backers participate. A similar positive effect exists when the first backers

[13] We only know of one empirical study of cross-group network effects on a CFP, namely Thies et al. (2018). As for other multisided platforms, most of the recent empirical work applies to media platforms (e.g., Wilbur, 2008; Sokullu, 2016), which are peculiar insofar as one group (advertisers) often exerts negative cross-group effects on the other group (viewers or readers). The only 'non-media' recent studies that we know of are the ones by Chu and Manchanda (2016) and Bounie, François, and Van Hove (2017) on consumer-to-consumer platforms and payment card platforms, respectively.

[14] Again, Thies et al. (2018) is the only paper that considers this issue for CFPs. Interestingly, Koh and Fichman (2014) show that on online business-to-business exchanges, the sign of the within-group network effects among buyers may depend on the level of activity on the platform. The effects are positive at low buying levels (possibly because buyers learn from other buyers' behavior) but negative at high buying levels (probably because competition intensifies among buyers).

attract subsequent backers either through direct solicitations or through word-of-mouth.[15] On the negative side, more backers may lead to increased competition for a limited number of rewards. Indeed, entrepreneurs typically propose a menu of rewards, with some rewards being offered in limited numbers. This may create a form of rationing, forcing some backers to select in the menu a reward different from the one that they initially hoped to receive.[16] Negative within-group network effects may also exist across different types of backers.[17]

Finally, the overall participation on a CFP (from entrepreneurs and backers alike) has the potential to make this CFP more attractive, thereby generating what can be called 'platform-wide network effects'. Such effects may stem from two main sources. First, a collective-attention effect may exist at the level of the platform: the more participants a CFP attracts, the larger its market share in the crowdfunding market, the more attention it will receive in the media and in social networks, which contributes to attract even more participants. Second, by managing more participants and more interaction among them, a CFP may move up the learning curve and gradually improve its operations and services, which makes it more attractive for new users.[18]

In sum, new backers are drawn to a CFP as a result of network effects related to participation. On the one hand, the combination of bidirectional positive cross-group network effects between entrepreneurs and backers creates an attraction loop, which draws more backers (and more entrepreneurs) to the CFP. On the other hand, positive within-group network effects in the group of backers and positive platform-wide network effects contribute to buttress this attraction loop. As a result, the total contributions on the CFP grows. *One potential consequence of this growth is the existence of positive inter-project network effects or, in other words, a form of*

[15] Smith, Windmeijer, and Wright (2015) show the existence of such positive within-group network effects in charitable giving.

[16] Similarly, competition between backers is likely to exist for equity-based crowdfunding, since there the entrepreneur always sells a limited number of shares.

[17] Lin, Sias, and Wei (2017) show that institutional investors tend to discourage retail investors (who have typically less expertise) to participate on Prosper.com. The authors exploit the fact that the platform started to identify institutional investors in May 2008 (whereas, before that date, all investors were labeled the same). In a similar vein, Liu (2017) finds that in general the producers of low-quality apps exert a negative within-group network effect on the producers of high-quality apps on both Apple and Google app stores.

[18] Jiang et al. (2018) suggest that such effects may be at work. The authors report that larger marketplace lending platforms tend to further increase their market share, as subsequent lenders are more likely to join a platform the larger its current base of lenders. The authors cannot, however, disentangle the sources of this effect (collective attention or improved operations).

complementarity between contemporaneous projects listed on a CFP. This is one hypothesis that we test in our empirical analysis, along with other hypotheses, which we now outline.

2.4. Testable hypotheses

To unbundle the web of network effects on a CFP, we start by deriving testable hypotheses on network effects related to usage. For this type of network effects within the group of backers, we distinguished between intra-project and inter-project network effects. We argued that intra-project network effects can go both directions: positive (because of herding, or of the goal-gradient effect) or negative (because of free-riding). The amplitude of these effects is thus empirically determined by whether the positive forces dominate the negative ones, and vice versa. If the positive forces dominate, our first hypothesis is as follows:

Hypothesis 1a (*Positive intra-project network effects*) Backers' contributions to a particular project increase future contributions to that project.

Conversely, if the negative forces outweigh the positive ones, we have the following alternative hypothesis:

Hypothesis 1b (*Negative intra-project network effects*) Backers' contributions to a particular project decrease future contributions to that project.

Regarding inter-project network effects, we argued above that they are expected to be negative if the set of backers and their willingness to contribute are fixed, making competition fiercer. We therefore propose the following hypothesis:

Hypothesis 2a (*Negative inter-project network effects*) Backers' contributions to other projects decrease future contributions to a given project.

However, inter-project network effects could be positive if the CFP manages to grow the volume of contributions it attracts over time. In this case, the hypothesis is as follows:

Hypothesis 2b (*Positive inter-project network effects*) Backers' contributions to other projects increase future contributions to a given project.

We can also refine Hypotheses 2a and 2b by splitting the 'other projects' according to whether or not they belong to the same category as the project under review. The sign of the inter-project network effects is then evaluated for the contributions to the other projects belonging to the same category or to different categories.

The above testable hypotheses on the direction and magnitude of network effects related to usage lead to our second set of hypotheses on network effects related to participation. In particular, if inter-project network effects are positive, this indicates that the CFP is in expansion and that a positive feedback loop is at work (and possibly positive platform-wide network effects as well). Our first task is then to check that the CFP is indeed growing. As total contributions may grow because new backers join the platform or because existing backers intensify their usage, we test the following two hypotheses:

Hypothesis 3a (*Increased backers participation*) Backers' contributions grow at a positive rate across the CFP.

Hypothesis 3b (*Increased backers usage*) Existing backers are more likely to contribute again in the CFP.

Our next task is to uncover the sources of the CFP expansion. In particular, we want to look beyond Hypothesis 3b and understand what drives existing backers to contribute again, thereby becoming 'recurrent backers'. In the previous section, we identified two channels: positive within-group network effects in the group of backers (the more backers there are, the more likely it is that projects will be funded and thus, that backers will get compensated), and positive cross-group effects from entrepreneurs to backers (the more entrepreneurs there are, the higher the chances that backers will find a project of their liking). Hence, we formulate the following two hypotheses:

Hypothesis 4a (*Positive within-group network effects for backers*) Recurrent backers are more likely to contribute again on a particular day the higher the number of backers that day.

Hypothesis 4b (*Positive cross-group network effects from entrepreneurs to backers*) Recurrent backers are more likely to contribute again on a particular day the higher the number of entrepreneurs (or projects posted) that day.

Two remarks are in order regarding the last set of hypotheses. First, we cannot test similar hypotheses on positive network effects related to participation of *new* backers. The reason is that we only have information on the identity and contributions of backers participating in the CFP we are considering. We are thus unable to observe the decisions of the new backers before they decide to participate in that CFP. Second, for the same reason, we do not address the network effects related to participation of *entrepreneurs* of the CFP (that is, the within-group network effects in that group, or the cross-group network effects that backers may exert on entrepreneurs).

3. Ulule: Background and Data

Opened to the public in July 2010, Ulule (www.ulule.com) has rapidly grown as the largest CFP in France and as a leading CFP in Europe. By August 2018, Ulule attracted more than 2.2 million registered members and facilitated the financing of over 24,000 projects. Since its inception, Ulule has become an important source of capital for early startups, especially in the arts and creativity-based industries (e.g., recorded music, film, video games).

Before projects are launched online on the platform, the Ulule team reviews all submitted project proposals. Accepted projects have either a presale objective (a specific product is typically offered for which the entrepreneur needs a minimum presales to start production) or a financial objective (the entrepreneur sets ex ante the minimum capital requirement to bring her entrepreneurial project to life). In the parlance of crowdfunding, Ulule uses an All-or-Nothing (AoN) reward-based scheme[19] in which entrepreneurs receive the proceeds of their campaign only if the objective is reached (they receive nothing otherwise). Ulule relies on a standard fee structure by charging a commission rate (starting at 6.67% on the first tranche and decreasing to 4.17% on the last tranche), which only applies to the amounts collected by successful projects.

Our dataset contains all information at the disposal of Ulule about entrepreneurs and backers. Critical for our purpose, we can trace the exact time at which all backers registered with the CFP, the projects they contributed to and the exact amounts they pledged to these projects. Our sample contains all projects posted on Ulule between July 5, 2010 and November 29, 2016. The sample covers the pledge decisions of more than 1.3 million backers on 23,971 projects, out of which 62% were successfully funded.

[19] Financial rewards are not allowed.

Table 1 provides summary statistics for the universe of Ulule projects. The first set of variables measures the various network effects depicted in the previous section. These variables capture the number of daily contributions within each project, as well as the number of daily contributions across all the other projects (category-wide or platform-wide). Similarly constructed variables capture instead the volume of contributions (i.e., €-amount). The average number of daily contributions per campaign is approximately 1.6, with a significant dispersion (standard deviation of 9.5). In terms of volume, the average daily amount of contributions is about €80, with a median of €5 and a standard deviation of €521. As for the number of the other category-wide (platform-wide) contributions, the average is approximately 97 (837) and the standard deviation is 104 (512). Again, similar insights apply for the volume of the other category/platform-wide contributions.

[Insert Table 1 about here]

The second set of variables includes time-varying project-level characteristics that have been shown to affect the likelihood of backers to pledge money on a project. We control for competition among projects within each category. We count 63 projects on average active at the same time per category. The ratio of the amount raised as compared to the targeted goal revolves around 50% on average, with a standard deviation of 46%. We also control for whether the project is featured by Ulule on its home page on a particular day (i.e., 2.2% of the projects on average). Lastly, we control for the proportion of recurrent backers contributing to a project during a day. The average proportion of recurrent backers per project per day is 12.7%, with a median of 0% and a standard deviation of 28.6%.

In Table 2, we report statistics about both the number and the volume of contributions for each of the 15 Ulule categories. The categories 'Charities & Citizen', 'Film & Video', 'Music', and 'Publishing & Journalism' are the largest in terms of total contributions. The average number of daily contributions varies quite significantly across categories. The category 'Sports' shows the lowest activity (approximately 1 contribution per project/day, with a standard deviation of 2.6) and the category 'Games' seems to be the most active (average daily contributions per project of 3.5, with a standard deviation of 16.2). This is also confirmed when we compare the average €-amount pledged on a daily basis in these categories. Distinguishing the number of both recurrent and new backers highlights that some categories are more effective at incentivizing backers to come back on the platform, particularly the categories ‘Comics’ and ‘Games’. In Table 3, we go one step further to describe cross-category dynamics. We track the number of contributions made by recurrent backers from one category (row values) to another (column values). The values in the diagonal are backers’ recursiveness within the same category or within the same project. Again, the matrix paints a consistent picture: some categories are more independent than others. This is the case of the category ‘Games’, of which 56% of contributions are made by recurrent backers and relatively few of them (32.6%) contribute in other categories. In general, a meaningful proportion of backers tend to pledge money repeatedly on the same project (bold values of the diagonal).

[Insert Tables 2 and 3 about here]

4. Empirical Analysis

4.1. Network effects related to usage

4.1.1. Intra- and inter-project network effects

We begin our analysis of network effects related to usage on project funding dynamics by decomposing intra- and inter-project network effects. We estimate the following within group specification:

$$y_{ijt} = \alpha_i + \alpha_t + \beta_1 Y_{i,t-1} + \beta_2 Y_{-i,t-1} + \beta_3 Y_{-j,t-1} + \boldsymbol{\gamma} \boldsymbol{X}_{i,t-1} + \varepsilon_{it}, \quad (1)$$

in which i denotes a project, $-i$ the active projects within the category of project i, $-j$ the active projects across all categories but the category of project i, and t a day. The dependent variable, y_{ijt}, is the number of contributions received by project i during the t^{th} day (in natural log scale); α_i and α_t represent a full set of project and time fixed effects. The project fixed effects α_i ensure that our results are not driven by time-invariant characteristics of the project, while funding cycle day fixed effects, among other time fixed effects α_t, account for campaign-level dynamics.[20] $Y_{i,t-1}$ is the number of backers’ contributions that project i has received by the end of day $t-1$

[20] Of course, our data are unlikely to capture every source of heterogeneity across projects. However, assuming that unobservable heterogeneity across projects α_i is time-invariant is reasonable in the Ulule setting because project characteristics are unlikely to change over the campaign, and project attributes are generally determined at the start of the campaign.

(in natural log scale). $Y_{-i,t-1}$ and $Y_{-j,t-1}$ are the number of backers' contributions that projects referenced respectively by $-i$ and $-j$ have generated by the end of day $t-1$ (in natural log scale). $\boldsymbol{X}_{i,t-1}$ is a vector of control variables and ε_{it} is the error term.[21] The vector of control variables takes into account time-varying project-level characteristics (namely, #projects, %goal, Popular, %recurrent backers). The coefficient of interest, β_1, measures intra-project network effects on the number of contributions received by a particular project, while the coefficients of interests, β_2 and β_3, measure inter-project network effects. In all cases, standard errors are adjusted for heteroskedasticity and clustered at the project level. It is important to note that we choose contributions of the past day as our main explanatory variables because this is the default information that Ulule provides backers with.[22]

Table 4 reports the coefficients of fixed-effect regression models derived from specification 1. We first estimate intra- and inter-project network effects separately. In column 1, we estimate intra-project network effects besides the full set of control variables and fixed effects. The coefficient of interest (β_1 in specification 1 above) is positive and significant at the 1% level. In columns 2 and 3, we run the same regression specification as in column 1 by considering inter-project network effects instead. Column 2 estimates inter-project network effects within categories, while column 3 looks at inter-project network effects across categories. The results are in line, with β_2 and β_3 both positive and significant at the 1% level. Next, in column 4, we estimate the same specification but we consider intra- and inter-project network effects together. The results are unchanged: β_1, β_2, and β_3 are positive and significant. In column 5, we go on by investigating the differential network effects across each of the 15 Ulule categories on project funding outcomes. Again, the estimates of the coefficients of interest are positive and significant.

Across columns 1-5, the coefficients of intra- and inter-project network effects are positive, always statistically significant at the 1% level, and have similar magnitudes. The respective

[21] One identification assumption behind equation 1 is that the lagged dependent variable and all other lagged independent variables are orthogonal to contemporaneous and future error terms, and that the error term ε_{it} is serially uncorrelated. However, if the error ε_{it} is serially correlated, it may be correlated with the lagged variables through past shocks, thus causing an endogeneity problem for estimation. We deal with this concern using a GMM framework, which is discussed below.

[22] By default, Ulule ranks projects according to a 'Popularity' index, which is based on the contributions collected on the previous day. Although backers have the possibility to opt for other rankings (e.g., based on the sum of past contributions), very few of them are reported to do so. It is thus fair to assume that only contributions of the past day are capable of affecting current contributions.

contributions of intra- and inter-project network effects have large economic consequences. Using results from column 4, a 10% increase in the number of contributions on project i results in a 1.72% increase in the number of contributions the day after on the same project i while holding all other variables constant.[23] This result confirms the findings of prior works (cited in section 2) documenting intra-project network effects in a similar way. However, the novelty here is the identification of sizeable inter-project network effects. Specifically, using again the results from column 4, a 10% increase in the number of contributions within (across) categories on a particular day subsequently leads to a 0.11% (0.42%) increase in the number of contributions on a project.[24] Furthermore, the results from column 5 indicate that some categories generate relatively more inter-project network effects than other categories. For example, the categories 'Music' and 'Art & Photos', with large and significant coefficients, exhibit more pronounced inter-project network effects across categories, whereas the category 'Games' is rather insulated with an estimated coefficient small and insignificant. This, by no means, implies that a category like 'Games' cannot thrive on the CFP. Rather, such category by attracting a crowd of specialized backers generates inter-project network effects but only within the category itself.

Next we gauge whether intra- and inter-project network effects play a differentiated role on the financing behavior of backers, whether they are recurrent or new. In columns 6-9, we replicate the specifications in columns 4 and 5 with the dependent variable either restricted to contributions made by recurring backers (i.e., backers having previously contributed at least once in any another projects) or to contributions by new backers on Ulule. The results are in line with those presented so far, though coefficient estimates of intra- and inter-project network effects display a higher order of magnitude for new backers. This suggests that new backers represent the bulk of network effects on the CFP. This finding is consistent with the idea that new backers are less sophisticated than recurrent backers and thus more prone to base their decisions on the observation of other backers' past behavior.

The evidence from control variables throughout specifications of Table 4 shows that the number of active projects within categories negatively impacts the number of contributions received.

[23] Recalling that we have a log-log model, this implies that a 10% increase in $Y_{i,t-1}$ multiplies y_{ijt} by $e^{0.179*} \approx 1.0172$.

[24] That is, a 10% increase in $Y_{-i,t-1}$ multiplies y_{ijt} by $e^{0.012*\ln(1.1)} \approx 1.0011$, and a 10% increase in $Y_{-j,t-1}$ multiplies y_{ijt} by $e^{0.044*\ln(1.1)} \approx 1.0042$.

Interestingly, this suggests that the number of projects active within a category reduces the number of contributions available per project, thereby leading to enhanced competition for pledges by entrepreneurs. The other control variables indicate that the number of contributions received is higher when the campaign is approaching its funding goal, consistent with the goal-gradient effect as documented by Kuppuswamy and Bayus (2017b). Projects being part of the ones featured on the first page of Ulule, and also the ones having a higher fraction of recurrent backers, appear to generate more contributions.

[Insert Table 4 about here]

Table A1 in the appendix probes the robustness of our results to an alternative definition of the variables of interest. We focus on the volume of contributions (i.e., €-amount) instead of the number of contributions. This alternative definition is useful for two reasons. First, it is not clear whether network effects only operate through an increase in the number of backers per project or also through an increase in the backers' willingness to pay for the project. Second, exploring the volume of contributions besides their sheer number may also highlight cross-sectional heterogeneity of the relationships, with network effects only affecting small-sized contributions. In Table A1, we mirror the specifications in columns 1-5 of Table 4 for the variables of interest in €-amount. Considering the volume of contributions does not change our prior conclusions, neither in significance nor in sign or order of magnitude.[25]

Collectively, these results supporting Hypotheses 1a and 2b strongly characterize (intra- and inter-project) network effects related to usage as being key drivers of project funding dynamics in CFPs.

[25] The within group estimates of the fixed-effect models of Table 4 have an asymptotic bias resulting from the failure of strict exogeneity in models with lagged dependent variables (Nickell, 1981; Alvarez and Arellano 2003). However, we expect this bias—also known as the Nickell bias—to be small in our setting as the time span is fairly large (about 36 days per campaign on average), which motivates the use of the model in Table 4 as the baseline. We deal with the Nickell bias using the Arellano and Bond (1991) GMM procedure. We look at both the number and volume of contributions and we include three-period lag as instrumental variables. Consistent with our expectations that the within group estimator has at most a small bias, the GMM estimates are similar to the ones reported in Table 4. In addition, the Arellano-Bond test for serial correlation does not reject the null of no second-order serial correlation, implying that the three-period lag is valid as an instrument. To conserve space, we do not report the estimation results.

4.1.2. Identifying inter-project network effects around fast starts

The systematic examination of network effects related to usage from the previous section revealed the existence of large *inter-project* network effects, which deserves further attention. In this section, we sharpen the identification of inter-project network effects on project funding outcomes using plausibly exogenous variation from 'fast starters'. This allows us to test Hypothesis 2b with more precision.

Our primary identifying assumption is that the identity of fast starters—that is, campaigns generating a very large number of contributions during their first day—is largely unexpected by backers, entrepreneurs, or platform managers and, thereby, is plausibly exogenous in our campaign sample. Consistent with this assumption, we find no evidence in the media that those campaigns experiencing a fast start were mentioned in Factiva in the weeks/months prior to their launch.[26] Then, we employ a difference-in-differences framework to estimate inter-project network effects on project funding outcomes.[27] Specifically, we estimate the following model:

$$y_{ijt} = \alpha_i + \alpha_t + \beta Fast\ start_t + \boldsymbol{\gamma X}_{i,t-1} + \varepsilon_{it}, \qquad (2)$$

in which y_{ijt} is the number of contributions received by project i during the t^{th} day (in natural log scale), α_i and α_t are respectively project and time fixed effects, $Fast\ start_t$ takes the value of one if during day t a project counts more than 200 (500, or 1,000) contributions in its first campaign day (zero otherwise), and $\boldsymbol{X}_{i,t-1}$ is the same set of project-level controls as before. Finally, ε_{it} denotes the error term, and the remaining Greek symbols are parameters to be estimated.

[Insert Table 5 about here]

This analysis presented in Table 5 yields three main results, which confirm Hypothesis 2b. First, we find that when a project experiences a fast start, the other contemporaneous projects benefit from it. Specifically, in odd-numbered columns of Panel A, we estimate the inter-project network effects generated on the CFP by fast starters and find that the coefficient of interest (β in

[26] Table A2 in the appendix reports the outcome of our search on Factiva.

[27] An important concern in difference-in-differences analyses is the possibility that another omitted factor that is relevant for the outcome variable of interest changes contemporaneously with the shock. However, this concern is somewhat mitigated in this setting given that our identification strategy relies on several shocks (occurring at different moments in time) to inter-project network effects. That is, one would have to find an unobserved contemporaneous change that systematically accompanies fast starters across the platform and over time.

specification 2) is always positive and significant at the 1% level. Using the results from column 1 shows that the day a project on the CFP attracts more than 200 contributions, this leads to a 1.82% increase in the number of daily contributions a particular project gets (i.e., by a multiple of $e^{0.018} = 1.0182$). This effect is stronger, the higher the number of contributions the fast starter generates: 2.84% (3.05%) increase if it gets more than 500 (1,000) contributions (column 3 (5)). Second, we find that the impact of fast starters is more pronounced on projects within their own category. In even-numbered columns of Panel A, we estimate the effect of fast starters within and across categories. When a project unexpectedly generates more than 200 contributions in its first day, it implies a 7.68% increase in the number of daily contributions received by the other projects within the same category, while it leads to a 1.31% increase for projects outside the category (using estimates from column 2). Third, when we restrict the dependent variable to contributions pledged by either recurring backers or new backers, we find that inter-project network effects generated by fast starters are roughly the same. From the results reported in Panel B of Table 5, one can see that coefficient estimates on $Fast\ start$ are of similar magnitudes in both cases.[28]

4.2. Network effects related to participation

4.2.1. Platform growth

As explained in section 2, the presence of positive inter-project network effects suggests that the total contributions on the platform is sufficiently growing, so as to overcome the fact that contemporaneous projects compete for funding. We want thus to examine more closely Ulule's expansion, which can result from the combination of positive cross-group network effects and/or platform-wide network effects.

Figure 1 plots the monthly evolution of the number of both new and recurrent backers through the sample period; Table 6 Panel A summarizes daily growth rates. There are significant variations in the number of backers. During July 2010 to December 2011, the average number of new and recurrent backers on a month was 648 and 133, respectively. Monthly new (recurrent) backers reached four digits in 2012 (early 2013). The CFP really started to take off in 2015—nearly 11,000 recurrent backers and 23,000 new backers each month, and about 400 thousands

[28] These results are robust to the use of the volume of contributions (in €-amount) instead of the number of contributions as variables of interest (see Table A3 in the appendix).

backers (both recurrent and new) visiting the CFP in that year. Since then, backer numbers continued to grow, except during months of July and August. Column 1 of Table 6 Panel A reports a compound daily growth rate of backers' number of contributions over the sample period of 0.25% (i.e., approximately 172% on an annual basis[29]). The growth rate does change over time and, as expected, is higher at the beginning of the sample period (i.e., 0.56% in 2010) but continues to be meaningful and positive six years later (i.e., 0.14% in 2015). The same goes for growth rates of backers' volume of contribution (see column 4). In addition, the growth rates of contributions tend to be higher for new backers than for recurrent backers. The remaining growth rates reported in Panel A concern each category separately. Consistent with our discussion above, certain categories, like 'Comics' and 'Games', exhibit a relatively high growth rate for recurrent backers' contributions than for recurrent backers' contributions in other categories. These statistics show that both recurrent and new backers contribute to the growth of the CFP.

[Insert Figure 1 and Table 6 about here]

Next, we test whether existing backers are likely to pledge money again on a project (Hypothesis 3b). To this end, we concentrate our analysis on backers who have contributed for the first time on the CFP the day of a 'fast start' (as defined in Table A2). Then we compare the propensity to contribute again of these backers with the propensity of backers who have contributed during another day on the platform. Panel B presents the results of tests of difference in means of the probability of re-contributing for backers whose first contribution occurred during a 'fast starter' day and other backers having contributed another day—namely, 7 days before the fast start (column 2), 30 days before (column 3), or 90 days after (column 4). The results across columns 2-4 indicate that the probability of contributing again is higher for backers having contributed when a fast starter was present on the CFP. To give an economic sense, this probability increases by 2.4 percentage points if the backer pledges money on a project during a 'fast starter' day (using the results from column 2). This suggests that fast starters can be seen as an engine for platform growth as they lead to recurrent contributions much more than other projects (and these recurrent contributions benefit other contemporaneous projects). In Panel B, we also replicate

[29] That is, $(0.0027 + 1)^{365} - 1 = 171.99\%$.

this analysis using the number of subsequent contributions instead of the probability of re-contributing. Our conclusions are unchanged.

In summary, our evidence in favor of our Hypotheses 3a and 3b, suggests that the CFP is growing and that part of this growth also comes from existing backers deciding to contribute again (especially after fast starts). As the growth of the CFP can result from within- and cross-*group* network effects, we turn to examining this possibility in the multivariate setting to follow.

4.2.2. Within- and cross-group network effects

To study network effects stemming from increased participation by backers, we perform linear regressions of the following specification:

$$y_k = \alpha + \beta_1 Y_{-k} + \beta_2 Y_i + \boldsymbol{\gamma} \boldsymbol{X}_k + \varepsilon_k. \quad (3)$$

Here y_k is one of our three measures of backer's k propensity to contribute again after having contributed once, α is a constant term, Y_{-k} is the number of the other backers present on the CFP the day a backer k contributed for the first time, and Y_i is the number of entrepreneurs running a campaign (i.e., the number of projects i active) on the CFP the day a backer k contributed for the first time (in natural log scale). The vector $\boldsymbol{X}_k$ contains a variety of factors, controlling for backer's age, backer's first project €-amount pledged, backer's country of residence, project fixed effects, and various time fixed effects (i.e., month, year, day of the week, and funding cycle day); ε_k denotes the error term. The coefficient of interest β_1 measures within-group network effects on backers' propensity to re-contribute, while the coefficient β_2 captures cross-group network effects. Statistical inference is based on heteroskedasticity-robust standard errors clustered by backer since we are collapsing the data at this level.[30]

Table 7 reports our regressions, estimates of equation 3. The results across columns 1-6 show clear support for Hypothesis 4b (positive cross-group network effects) but not for Hypothesis 4a (positive within-group network effects). First, we estimate both within-group and cross-group network effects on the probability that a backer contributes again after having contributed once, with the full set of fixed effects in column 1 and the further addition of control variables in column 2. In both columns, the coefficient of interest β_1 in Specification 3 turns out to be

[30] It is important to note that all our results survive if we cluster the standard errors at the project or project-year levels, rather than at the backer level. These results can be obtained upon request.

negative, while β_2 is positive. Second, we employ alternative dependent variables capturing the backers' propensity to re-contribute, namely the total number (volume) of contributions that backers add up subsequently (i.e., after having contributed once). Across columns 3-6, we estimate again both within-group and cross-group network effects and find qualitatively similar results than in columns 1 and 2.

The cross-group network effects are economically meaningful. A one standard deviation increase in the logged number of projects active on the CFP the day any backers contributed for the first time (which is equal to 0.58 in this sample) is associated with an increase in backers' probability to contribute again by 42.1% (using the coefficient estimate from column 2). However, these cross-group network effects on backers' probability to re-contribute are mitigated by the economic significance of within-group network effects. Again from column 2, a one standard deviation change in the logged number of backers present on the CFP the day any backers contributed for the first time (which is equal to 0.86 in this sample) is associated with a drop in backers' probability to re-contribute by 49.3%.

Overall, our results in this section show that the quantity of projects proposed on the CFP enhances existing backers' participation, suggesting that cross-group (from entrepreneurs to existing backers) network effects fuel the growth of the CFP we documented previously. In contrast, within-group (from backers to backers) network effects deter backers from contributing again on the CFP. This is broadly consistent with the category-level findings of Thies et al. (2018).[31]

[Insert Table 7 about here]

5. Conclusion

This study adds to the literature on FinTech and sharing economy by providing empirical estimates of the extent of networks effects in crowdfunding. By disentangling the web of network effects at work in a leading European CFP, our findings inform about the most

[31] Of course, other types of cross-group network effects could also fuel the growth of the CFP. As noted at the end of section 2, our setting only allows us to identify cross-group network effects going from the group of entrepreneurs to the group of (existing) backers. We leave for future research the empirical assessment of other types of cross-group network effects.

fundamental determinants of both the rise of digital platforms and competition among these platforms. This is of interest to academic researchers and policymakers alike.

Reward-based crowdfunding is important to look at in its own right as a sizeable channel of raising money for early startups, particularly in creativity-based industries. It also provides an excellent setting to examine network effects that relate to both participation and usage decisions because it offers an environment in which a very large population of backers can observe the contributions of others within and across projects listed on the CFP. At the same time, reward-based CFPs share important characteristics with other FinTech platforms, such as marketplace lending platforms, token-based platforms.

The richness of our data shows that network effects conflate in a complex way. First, we document that network effects stemming from increased usage are pervasive on the CFP. Besides the meaningful role of intra-project network effects already documented in prior work, our evidence uncovers that inter-project network effects also represent non-negligible sources of funding success dynamics. Second, we show that network effects related to participation decisions do increase the size of the CFP. More specifically, we find that the larger the size the group of entrepreneurs (as captured by the number of projects), the higher the propensity of backers to pledge again on the same CFP. This evidence suggests that cross-group (from entrepreneurs to backers) network effects are at play, potentially creating a positive feedback loop boosting the growth of the CFP. However, we also find that the prevalence of cross-group network effects is somewhat mitigated by within-group (from backers to backers) network effects going in the opposite direction.

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Table A1. Intra- and inter-project network effects: €-value of contributions

This table presents fixed-effects estimates of the intra- and inter-project effects on the €-value of contributions received by projects over their funding cycle. The dependent variable, €-value contributions$_i$, is the total value (in €) of contributions received by project *i* during a day (in log). The lag of the dependent variable captures intra-project effects. €-value contributions$_{-i}$ is the total value (in €) of contributions received by projects referenced in the same category of project i during a day except the project *i* itself (in log) and captures inter-project effects within categories. €-value contributions$_{-j}$ is the total value (in €) of contributions received by projects referenced in all other categories during a day except the category of project *i* itself (in log) and captures inter-project effects across categories. Control variables include # projects$_i$, % goal, Popular, % recurrent backers. # projects$_i$ is the number of projects within category *i* (in log). % goal is the ratio of the amount raised to targeted goal during a day, Popular is a dummy variable equal to 1 if the project is among the 8 projects having attracted the highest number of backers during a day and 0 otherwise, % recurrent backers is the ratio of number of recurrent backers to the total number of backers on a project during a day (‘recurrent’ means having contributed previously at least once in any another projects). The sample contains all projects posted on the Ulule platform between 5 July 2010 and 29 November 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by project. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	€-value contributions$_i$				
	(1)	(2)	(3)	(4)	(5)
€-value contributions$_{i,t-1}$	0.097***			0.097***	0.096***
	(0.001)			(0.001)	(0.001)
€-value contributions$_{-i,t}$		0.026***		0.017***	
		(0.003)		(0.003)	
€-value contributions$_{-j,t}$			0.120***	0.090***	
			(0.007)	(0.007)	
€-value contributions$_{Art\ \&Photo,t-1}$					0.016***
					(0.003)
€-value contributions$_{Charities\ \&\ Citizen,t-1}$					0.018***
					(0.004)
€-value contributions$_{Childhood\ \&\ Education,t-1}$					0.008***
					(0.002)
€-value contributions$_{Comics,t-1}$					0.010***
					(0.002)
€-value contributions$_{Crafts\ \&\ Food,t-1}$					0.010***
					(0.002)
€-value contributions$_{Fashion\ \&\ Design,t-1}$					0.001
					(0.002)
€-value contributions$_{Film\ \&\ Video,t-1}$					0.009**
					(0.004)
€-value contributions$_{Games,t-1}$					0.003
					(0.002)
€-value contributions$_{Heritage,t-1}$					0.004*
					(0.002)
€-value contributions$_{Music,t-1}$					0.027***
					(0.004)
€-value contributions$_{Other,t-1}$					0.005***
					(0.002)
€-value contributions$_{Publishing\ \&\ Journalism,t-1}$					0.011***
					(0.003)
€-value contributions$_{Sports,t-1}$					0.010***
					(0.002)
€-value contributions$_{Stage,t-1}$					0.021***

					(0.003)
€-value contributions$_{Technology,t-1}$					0.001
					(0.002)
# projects$_{i,t}$	0.015	-0.021	-0.022	-0.040*	-0.051**
	(0.023)	(0.026)	(0.026)	(0.024)	(0.024)
% goal$_t$	1.403***	1.571***	1.569***	1.401***	1.400***
	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)
Popular$_t$	2.044***	2.121***	2.124***	2.048***	2.050***
	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)
% recurrent backers$_t$	2.611***	2.632***	2.632***	2.610***	2.610***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Project Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes	Yes
# observations	814,960	814,960	814,960	814,960	814,951
# projects	23,022	23,022	23,022	23,022	23,022
R^2	0.466	0.460	0.460	0.466	0.466

Table A2. Projects with fast start (>200 contributions the first day)

This table reports information about projects having experienced a fast start (i.e., more than 200 contributions the first day). It reports name, category, date, number of contributions and final amount raised by these projects. The last three columns present media coverage (based on Factiva search) on these projects. This search has been restricted in time (i.e., prior the campaign launch) but also not restricted in time.

Project Name	Category	Start date	Day 1 # contributions	Final amount raised	Factiva search outcome: Not restricted in time	Factiva search outcome: Prior to campaign launch	Links
Version studio of "Never Enough"	Music	October 22, 2012	254	3,213	0	0	
Un bouquet geant pour Christiane Taubira !	Charities & Citizen	February 1, 2013	947	12,302	3	0	
Noob, le film !	Film & Video	May 3, 2013	371	681,046	36	0	
Hors-Serie	Publishing & Journalism	March 12, 2014	312	76,416	9	0	
L'Appel de Cthulhu, 7e edition francaise	Games	February 23, 2015	600	402,985	3	0	
Gold Quest	Games	May 18, 2015	280	22,236	0	0	
Bruti	Games	May 20, 2015	220	68,123	1	0	
Guide Complet Zelda	Games	May 7, 2015	206	17,683	1	0	
Hero Corp Saison 5	Film & Video	August 10, 2015	1,667	200,887	4	0	
NeoRetro, the timeless telephone	Fashion & Design	June 22, 2015	266	84,403	7	1	www.toutsurmesfinances.com/placements
BREUM	Comics	September 4, 2015	203	24,314	0	0	
CHROMA - Saison 1	Film & Video	October 22, 2015	4,105	206,006	0	0	
Comme convenu.	Comics	October 6, 2015	2,085	264,174	4	0	
Soutenez @rret sur images, @si vous le rendra	Publishing & Journalism	November 5, 2015	1,437	271,044	0	0	
Les Fatals Picards	Music	February 1, 2016	809	92,855	5	0	
L'Appel de Cthulhu - Les 5 Supplices	Games	November 23, 2015	410	196,861	3	0	
DTC. (Dans Ton Com'.)	Charities & Citizen	December 17, 2015	683	16,989	3	0	
Le Kit du Jardinier-Maraicher	Film & Video	February 15, 2016	312	50,412	0	0	
UNKNOWN MOVIES : SAISON 3	Film & Video	March 11, 2016	244	42,462	0	0	
Les Contrees du Reve	Games	May 12, 2016	595	201,140	0	0	
Zothique et autres mondes Clark Ashton Smith	Publishing & Journalism	May 17, 2016	290	83,493	0	0	
Guides Complets Zelda Link's Awakening	Games	June 13, 2016	227	19,884	1	0	
L'EQUATEUR PENCHE, DEUXIEME ÉTAPE	Film & Video	May 31, 2016	203	79,381	0	0	
Stupeflip. Nouvel Album. 3 Mars 2017.	Music	October 5, 2016	2,571	427,972	5	0	
Maliki Blog	Comics	October 4, 2016	1,394	272,900	3	0	
LE PULL PARFAIT	Fashion & Design	October 26, 2016	280	237,584	0	0	
PARANOIA	Games	November 16, 2016	284	59,693	2	0	

Table A3. Inter-project network effects around fast starts: €-value contributions

This table presents difference-in-differences estimates of the effect of project's fast starts on the €-value of contributions received by projects over their funding cycle. The dependent variable is €-value contributions$_i$. Fast start$_t$ is a dummy variable that is set to zero during a day a project counts more than 200 (500, or 1,000) contributions in its first campaign day. Similarly, Fast start$_{j(-j),t}$ is a dummy variable that is set to zero during a day a project counts more than 200 (500, or 1,000) contributions in its first campaign day within a category *j* (in other categories -*j*). These dummy variables capture the inter-project effects of a project's fast start (within and/or across categories). Appendix Table A2 reports the projects that experienced an unexpected fast start. Control variables include €-value contributions$_{-i,t-1}$, # projects$_i$, % goal, Popular, % recurrent backers and are defined as in Table 4. The sample contains all projects posted on the Ulule platform between 5 July 2010 and 29 November 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by project. *p*-values [in brackets] are from Wald tests assessing the statistical significance of differences between select coefficients. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	>200		>500		>1,000	
	(1)	(2)	(3)	(4)	(5)	(6)
Fast start$_t$	0.030**		0.062***		0.066**	
	(0.014)		(0.023)		(0.032)	
Fast start$_{j,t}$ [1]		0.092**		0.103		0.204**
		(0.047)		(0.069)		(0.098)
Fast start$_{-j,t}$ [2]		0.025*		0.058**		0.052
		(0.014)		(0.024)		(0.033)
p-value [1] = [2]		[0.173]		[0.532]		[0.142]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# observations	814,960	814,960	814,960	814,960	814,960	814,960
# projects	23,022	23,022	23,022	23,022	23,022	23,022
R^2	0.469	0.469	0.469	0.469	0.469	0.469

Figure 1. Backers by time

The figure presents the evolution of the number of both new and recurrent backers visiting Ulule between July 5, 2010 and November 29, 2016. The y-axis is number of backers (new and recurrent) and the x-axis is the time (monthly).

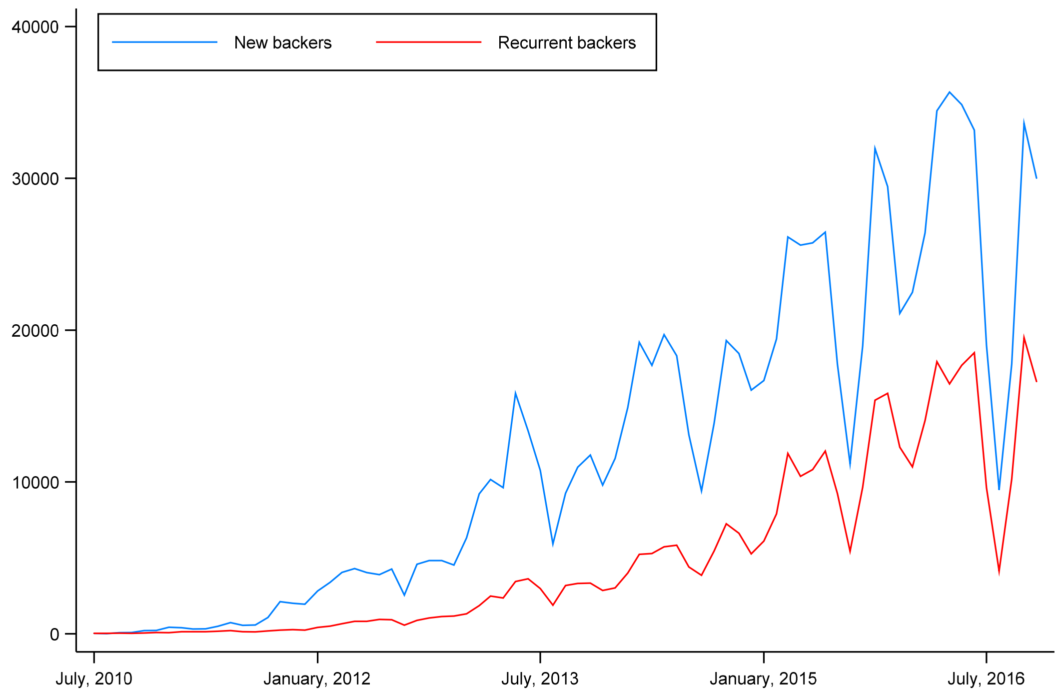

Table 1. Sample summary statistics

The table presents summary statistics for the main variables used in the analyses. The sample includes the universe of projects on the Ulule platform between July 5, 2010 and November 29, 2016. # contributions$_i$ is the number of contributions received by project *i* during a day. # contributions$_{-i}$ is the number of contributions received by projects referenced in the same category of project *i* during a day except the project *i* itself. # contributions$_{-j}$ is the number of contributions received by projects referenced in all other categories during a day except the category of project *i* itself. €-value contributions$_i$ is the total value (in €) of contributions received by project *i* during a day. €-value contributions$_{-i}$ is the total value (in €) of contributions received by projects referenced in the same category of project *i* during a day except the project *i* itself. €-value contributions$_{-j}$ is the total value (in €) of contributions received by projects referenced in all other categories during a day except the category of project *i* itself. # projects$_i$ is the number of projects within category *i*. % goal is the ratio of the amount raised to targeted goal during a day. Popular is a dummy variable equal to 1 if the project is among the 8 projects having attracted the highest number of backers during a particular day and 0 otherwise. % recurrent backers is the ratio of number of recurrent backers to the total number of backers on a project during a day ('recurrent' means having contributed previously at least once in any another projects).

Variable	Mean	Std dev	Median	Min	Max	# obs
Variables of interest						
# contributions$_i$	1.587	9.747	1.000	0.000	4,105.000	838,931
# contributions$_{-i}$	96.727	104.011	71.000	0.000	4,178.000	838,931
# contributions$_{-j}$	837.055	551.612	761.000	0.000	5,452.000	838,931
€-value contributions$_i$	79.899	511.822	5.000	0.000	109,874.000	838,931
€-value contributions$_{-i}$	4,790.567	5,277.181	3,435.276	0.000	121,840.500	838,931
€-value contributions$_{-j}$	42,653.110	28,938.600	37,688.400	0.000	221,388.600	838,931
Control variables						
# projects$_i$	63.159	46.243	53.000	1.000	219.000	838,931
% goal	0.500	0.451	0.370	0.005	2.257	838,931
Popular	0.022	0.148	0.000	0.000	1.000	838,931
% recurrent backers	0.127	0.286	0.000	0.000	1.000	838,931

Table 2. Contributions by category

The table presents statistics on contributions received by projects over their funding cycle by category. The sample includes the universe of projects on the Ulule platform between July 5, 2010 and November 29, 2016. The category classification is as reported by Ulule. Statistics on the number and total €-value of contributions per project/day by category are reported. # $contributions_i$ is the number of contributions received by project *i* during a day (# $contributions_i$ is also decomposed between the number of recurring backers (i.e., backers having previously contributed at least once in any another projects) and the new project-backers on the platform. €-value $contributions_i$ is the total value (in €) of contributions received by project *i* during a day.

Category	% total platform contributions	# $contributions_i$ (all)		# $contributions_i$ (recurrent)		# $contributions_i$ (new)		€-value $contributions_i$	
		Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
Art & Photo (1)	4.59%	1.382	3.166	0.386	1.293	0.996	2.303	68.714	266.214
Charities & Citizen (2)	15.71%	1.316	5.734	0.346	2.490	0.970	3.998	65.527	374.061
Childhood & Education (3)	3.39%	1.280	3.454	0.320	1.246	0.960	2.580	57.394	200.271
Comics (4)	5.82%	3.433	27.462	1.659	11.943	1.773	16.180	125.802	926.154
Crafts & Food (5)	4.38%	1.485	3.248	0.393	1.334	1.092	2.380	82.562	242.878
Fashion & Design (6)	3.68%	1.764	5.910	0.474	2.334	1.291	4.379	123.167	588.893
Film & Video (7)	16.40%	1.525	14.130	0.379	3.457	1.146	10.934	75.142	541.091
Games (8)	4.88%	3.472	16.198	1.944	12.304	1.529	6.110	211.210	1,480.725
Heritage (9)	1.39%	1.560	3.161	0.530	1.514	1.030	2.225	122.166	463.942
Music (10)	14.43%	1.563	9.748	0.399	3.417	1.164	6.661	67.257	427.202
Other (11)	3.68%	1.450	6.060	0.405	3.050	1.045	3.753	86.411	475.975
Publishing & Journalism (12)	10.26%	2.714	11.961	0.920	5.121	1.795	7.689	123.736	769.693
Sports (13)	3.54%	0.951	2.648	0.163	0.679	0.788	2.318	59.518	293.292
Stage (14)	6.02%	1.227	2.397	0.312	0.907	0.915	1.832	59.081	179.470
Technology (15)	1.81%	1.608	5.666	0.384	1.890	1.224	4.556	109.833	781.547
All categories	100.00%	1.587	9.747	0.464	3.848	1.123	6.668	79.899	511.822

Table 3. Cross-category dynamics: Ordered-pair matrix

This matrix presents the number of contributions per category conditional on backers' prior contributions. The categories are rank ordered by the number of contributions in each category. The row variables are the categories of origin, while the column variables are the categories of destination. Values in bold in the diagonal are backers' contributions going to the same project of origin. Values in the total column and row include all categories.

Category	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	Total
Art & Photo (1)	**3,447** 2,525	1,575	283	1,762	529	462	1,296	582	262	1,230	386	1,740	179	607	142	17,007
Charities & Citizen (2)	1,438	**12,321** 13,023	1,837	1,649	2,291	1,692	3,562	972	977	3,196	1,658	4,669	868	1,792	603	52,548
Childhood & Education (3)	268	1,600	**3,189** 870	395	326	275	575	203	155	605	425	903	148	326	102	10,365
Comics (4)	1,601	1,725	438	**3,630** 14,989	662	597	2,090	2,371	231	1,660	661	3,631	206	363	244	35,099
Crafts & Food (5)	483	2,182	369	642	**3,480** 1,550	739	939	400	247	959	553	1,142	196	442	259	14,582
Fashion & Design (6)	414	1,489	247	547	682	**3,122** 1,618	607	360	108	665	339	935	152	296	204	11,785
Film & Video (7)	1,855	5,165	851	3,589	1,328	1,056	**13,456** 18,544	1,992	453	5,305	1,370	4,950	565	2,760	734	63,973
Games (8)	503	1,014	213	2,720	426	384	1,431	**8,370** 16,159	116	999	374	2,909	127	232	324	36,301
Heritage (9)	192	807	181	178	250	132	298	105	**1,293** 779	342	191	515	90	257	33	5,643
Music (10)	1,212	3,635	705	1,623	1,059	834	3,523	800	424	**12,091** 15,185	922	3,003	427	2,321	328	48,092
Other (11)	349	1,495	344	595	420	414	785	262	193	791	**4,023** 620	920	178	392	130	11,911
Publishing & Journalism (12)	1,729	5,043	961	4,133	1,320	1,065	3,743	2,867	603	2,910	1,171	**7,017** 11,186	389	1,192	577	45,906
Sports (13)	199	932	161	187	265	208	435	112	108	438	247	499	**3,274** 979	221	75	8,340
Stage (14)	683	2,070	498	420	514	356	2,187	265	284	2,263	481	1,494	258	**5,848** 3,185	131	20,937
Technology (15)	166	902	124	415	316	233	742	569	78	392	258	792	77	149	**1,490** 402	7,105
Total	17,064	54,978	11,271	37,474	15,418	13,187	54,213	36,389	6,311	49,031	13,679	46,305	8,113	20,383	5,778	389,594
% cross-category recursiveness	65.0%	53.9%	64.0%	50.3%	67.4%	64.1%	41.0%	32.6%	67.2%	44.4%	66.1%	60.7%	47.6%	55.7%	67.3%	51.8%
% total contributions	27.9%	26.3%	24.9%	48.3%	26.4%	26.9%	24.8%	56.0%	34.0%	25.5%	27.9%	33.9%	17.2%	25.4%	23.9%	29.3%

Table 4. Intra- and inter-project network effects

This table presents fixed-effects estimates of the intra- and inter-project effects on the number of contributions received by projects over their funding cycle. The dependent variable, # contributions$_i$, is the number of contributions received by project *i* during a day (in log). In columns 1 to 5 the dependent variable is for all contributions, while the dependent variable is restricted to contributions made by recurring backers (i.e., backers having previously contributed at least once in any another projects) in columns 6 and 7 and to new project-backers on the platform in columns 8 and 9. The lag of the dependent variable captures intra-project effects. # contributions$_{-i}$ is the number of contributions received by projects referenced in the same category of project *i* during a day except the project *i* itself (in log) and captures inter-project effects within categories. # contributions$_{-j}$ is the number of contributions received by projects referenced in all other categories during a day except the category of project *i* itself (in log) and captures inter-project effects across categories. Control variables include # projects$_i$, % goal, Popular, % recurrent backers. # projects$_i$ is the number of projects within category *i* (in log). % goal is the ratio of the amount raised to targeted goal during a day, Popular is a dummy variable equal to 1 if the project is among the 8 projects having attracted the highest number of backers during a day and 0 otherwise, % recurrent backers is the ratio of number of recurrent backers to the total number of backers on a project during a day. The sample contains all projects posted on the Ulule platform between 5 July 2010 and 29 November 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by project. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	# contributions$_i$ (all)					# contributions$_i$ (recurrent)		# contributions$_i$ (new)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# contributions$_{i,t-1}$	0.181***			0.179***	0.179***	0.067***	0.067***	0.169***	0.169***
	(0.002)			(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
# contributions$_{-i,t-1}$		0.025***		0.012***		0.005***		0.011***	
		(0.002)		(0.002)		(0.001)		(0.002)	
# contributions$_{-j,t-1}$			0.072***	0.044***		0.010***		0.044***	
			(0.003)	(0.003)		(0.002)		(0.002)	
# contributions$_{\text{Art \&Photo},t-1}$					0.008***		0.001		0.008***
					(0.001)		(0.001)		(0.001)
# contributions$_{\text{Charities \& Citizen},t-1}$					0.008***		0.001		0.009***
					(0.002)		(0.001)		(0.002)
# contributions$_{\text{Childhood \& Education},t-1}$					0.001		0.000		0.001
					(0.001)		(0.001)		(0.001)
# contributions$_{\text{Comics},t-1}$					0.005***		0.002***		0.004***
					(0.001)		(0.001)		(0.001)
# contributions$_{\text{Crafts \& Food},t-1}$					0.005***		-0.000		0.006***
					(0.001)		(0.001)		(0.001)
# contributions$_{\text{Fashion \& Design},t-1}$					0.001		0.001		0.000
					(0.001)		(0.001)		(0.001)
# contributions$_{\text{Film \& Video},t-1}$					0.003*		0.001		0.003**
					(0.002)		(0.001)		(0.002)
# contributions$_{\text{Games},t-1}$					0.001		-0.000		0.001

					(0.001)		(0.001)		(0.001)
# contributions$_{Heritage,t-1}$					0.002*		0.001		0.002*
					(0.001)		(0.001)		(0.001)
# contributions$_{Music,t-1}$					0.014***		0.005***		0.013***
					(0.002)		(0.001)		(0.002)
# contributions$_{Other,t-1}$					0.004***		0.001**		0.003***
					(0.001)		(0.001)		(0.001)
# contributions$_{Publishing\ \&\ Journalism,t-1}$					0.004***		0.001		0.004***
					(0.001)		(0.001)		(0.001)
# contributions$_{Sports,t-1}$					0.004***		0.003***		0.003**
					(0.001)		(0.001)		(0.001)
# contributions$_{Stage,t-1}$					0.012***		0.002*		0.011***
					(0.002)		(0.001)		(0.002)
# contributions$_{Technology,t-1}$					0.003***		0.001**		0.001**
					(0.001)		(0.001)		(0.001)
# projects$_{i,t}$	0.001	- 0.028***	-0.023***	-0.027***	-0.026***	-0.010**	-0.008*	-0.027***	-0.027***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)	(0.004)	(0.007)	(0.007)
% goal$_t$	0.315***	0.397***	0.395***	0.314***	0.313***	0.150***	0.150***	0.238***	0.237***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)
Popular$_t$	1.139***	1.228***	1.230***	1.141***	1.142***	0.641***	0.641***	1.057***	1.057***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)
% recurrent backers$_t$	0.655***	0.669***	0.669***	0.655***	0.655***	0.647***	0.647***	0.111***	0.111***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Project Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	814,960	814,960	814,960	814,960	814,960	814,960	814,960	814,960	814,960
# projects	23,022	23,022	23,022	23,022	23,022	23,022	23,022	23,022	23,022
R^2	0.559	0.541	0.541	0.559	0.559	0.602	0.602	0.447	0.447

Table 5. Inter-project network effects around fast starts

This table presents difference-in-differences estimates of the effect of porject's fast starts on the number of contributions received by projects over their funding cycle. The dependent variable is # $contributions_i$. In Panel A, the dependent variable is for all contributions, while the dependent variable is restricted to contributions made by recurring backers (i.e., backers having previously contributed at least once in any another projects) and to new project-backers on the platform in Panel B. Fast $start_t$ is a dummy variable that is set to zero during a day a project counts more than 200 (500, or 1,000) contributions in its first campaign day. Similarly, Fast $start_{j(-j),t}$ is a dummy variable that is set to zero during a day a project counts more than 200 (500, or 1,000) contributions in its first campaign day within a category *j* (in other categories *-j*). These dummy variables capture the inter-project effects of a project's fast start (within and/or across categories). Appendix Table A2 reports the projects that experienced an unexpected fast start. Control variables included in the estimations but unreported for brevity are # $contributions_{-i,t-1}$, # $projects_i$, % goal, Popular, % recurrent backers and are defined as in Table 4. The sample contains all projects posted on the Ulule platform between 5 July 2010 and 29 November 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by project. *p*-values [in brackets] are from Wald tests assessing the statistical significance of differences between select coefficients. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: All contributions

	>200		>500		>1,000	
	(1)	(2)	(3)	(4)	(5)	(6)
Fast $start_t$	0.018***		0.028***		0.030***	
	(0.004)		(0.007)		(0.010)	
Fast $start_{j,t}$ [1]		0.074***		0.090***		0.123***
		(0.017)		(0.025)		(0.037)
Fast $start_{-j,t}$ [2]		0.013***		0.022***		0.021**
		(0.004)		(0.007)		(0.010)
p-value [1] = [2]		[0.001]		[0.008]		[0.008]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# observations	814,960	814,960	814,960	814,960	814,960	814,960
# projects	23,022	23,022	23,022	23,022	23,022	23,022
R^2	0.550	0.550	0.550	0.550	0.550	0.550

Panel B: Recurrent vs. new backers						
	>200		>500		>1,000	
	recurrent	new	recurrent	new	recurrent	new
	(1)	(2)	(3)	(4)	(5)	(6)
Fast start$_t$	0.013***	0.015***	0.020***	0.021***	0.026***	0.021**
	(0.003)	(0.004)	(0.005)	(0.007)	(0.007)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# observations	814,960	814,960	814,960	814,960	814,960	814,960
# projects	23,022	23,022	23,022	23,022	23,022	23,022
R^2	0.550	0.550	0.550	0.550	0.550	0.550

Table 6. Platform growth

This table presents statistics on growth rates. Panel A presents the compound daily growth rate of backers' contributions (in number and value) on the Ulule platform over the period between 5 July 2010 and 29 November 2016. Panel A also presents the growth rate of backers' contributions by year and by category. Panel B presents the results of *t*-test with unequal variances of the mean difference between backers having contributed for the first time at the 'Fast start' date and backers having contributed at another date: i.e., 7 days before the fast start in column 2, 30 days before the fast start in column 3, and 90 days after the fast start in column 4. Pr(# $\text{contributions}_{k,\text{Fast start++}}$ > 0) is the probability of contributing again for a backer *k* if its first contribution occurred at a 'Fast start' date, while # $\text{contributions}_{k,\text{Fast start++}}$ is defined similarly for a backer *k*'s number of subsequent contributions. Column 1 presents the mean of Pr(# $\text{contributions}_{k,\text{Fast start++}}$ > 0) and of # $\text{contributions}_{k,\text{Fast start++}}$ at the 'Fast start' date as reported in Table A2. *p*-values are in brackets. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Platform growth

Growth rate	# contributions	# contributions (recurrent)	# contributions (new)	€-value contributions
	(1)	(2)	(3)	(4)
Whole period across the platform	**0.25%**	**0.27%**	**0.24%**	**0.35%**
By year				
2010	0.56%	0.00%	0.64%	1.74%
2011	0.39%	0.38%	0.39%	0.44%
2012	0.33%	0.27%	0.35%	0.28%
2013	0.35%	0.23%	0.39%	0.39%
2014	0.25%	0.24%	0.25%	0.26%
2015	0.14%	0.18%	0.12%	0.20%
2016	0.51%	0.50%	0.51%	0.57%
By category				
Art & Photo (1)	0.20%	0.13%	0.19%	0.42%
Charities & Citizen (2)	0.20%	0.17%	0.19%	0.37%
Childhood & Education (3)	0.15%	0.08%	0.20%	0.25%
Comics (4)	0.26%	0.20%	0.24%	0.39%
Crafts & Food (5)	0.17%	0.02%	0.24%	0.29%
Fashion & Design (6)	0.24%	0.10%	0.24%	0.31%
Film & Video (7)	0.16%	0.09%	0.21%	0.29%
Games (8)	0.17%	0.17%	0.16%	0.21%
Heritage (9)	0.08%	0.00%	0.09%	0.10%
Music (10)	0.25%	0.15%	0.24%	0.30%
Other (11)	0.33%	0.09%	0.33%	0.48%
Publishing & Journalism (12)	0.24%	0.15%	0.26%	0.33%
Sports (13)	0.21%	0.04%	0.21%	0.24%
Stage (14)	0.20%	0.10%	0.20%	0.30%
Technology (15)	0.20%	0.06%	0.20%	0.24%

Panel B: Backers' recursiveness after fast starts

	Fast start_t	Fast $\text{start}_{-7\text{ days}}$	Fast $\text{start}_{-30\text{ days}}$	Fast $\text{start}_{+90\text{ days}}$
	(1)	(2)	(3)	(4)
Pr(# $\text{contributions}_{k,\text{Fast start++}}$ > 0)	0.170	0.146	0.166	0.143
Diff.		0.024***	0.004	0.027***
		[0.000]	[0.166]	[0.000]
# $\text{contributions}_{k,\text{Fast start++}}$	1.321	1.246	1.284	1.254
Diff.		0.074***	0.036***	0.066***
		[0.000]	[0.002]	[0.000]
# observations	38,527	21,092	18,938	14,415

Table 7. Within- and cross-group network effects

This table presents OLS estimates of the within- and cross-group effects on backers' propensity to re-contribute. In columns 1 and 2, the dependent variable, Pr(# contributions)$_k$, is equal to one if backer's *k* contribute again after having contributed once, and zero otherwise. In columns 3 and 4, the dependent variable, # contributions$_k$, is the number of contributions backer's *k* adds up (in log). In columns 5 and 6, the dependent variable, €-value contributions$_k$, is the total value (in €) of contributions backer's *k* adds up (in log). # backers$_{-k}$ is the number of the other backers present on the Ulule platform the day a backer *k* contributed for the first time (in log) and captures within-group effects. # projects$_i$ is the number of projects *i* active on the Ulule platform the day a backer *k* contributed for the first time (in log) and captures cross-group effects. Control variables included in the estimation of columns 2, 4, and 6 but unreported for brevity are Age, €-value first contribution (in log), and Country of residence. All the models include a constant, whose coefficient is not reported. The sample comprises all backers participating on the Ulule platform between 5 July 2010 and 29 November 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by backer. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Pr(# contributions > 1)$_k$		# contributions$_k$		€-value contributions$_k$	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample mean	*0.1896*		*0.1823*		*3.4962*	
# backers$_{-k}$	-0.113***	-0.108***	-0.105***	-0.102***	-0.126***	-0.114***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
# projects$_i$	0.145***	0.137***	0.132***	0.119***	0.153***	0.134***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.010)	(0.007)
Controls	No	Yes	No	Yes	No	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# observations	941,000	621,806	941,000	621,806	941,000	621,806
R^2	0.152	0.280	0.176	0.326	0.192	0.763