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Crowdfunding Dynamics

Abstract

Various forms of social learning and network effects are at work on crowdfunding platforms, giving rise to informational and payoff externalities. We use novel entrepreneur-backer data to study how these externalities shape funding dynamics, within and across projects. We find that backers decide to back a particular project based on past contributions not only to that project—as documented by prior work—but also to other contemporaneous projects—a novel result. Our difference-in-differences estimates indicate that such 'cross-project funding dynamics' account for 4-5% in the increase of contributions that projects generate on a daily basis. We show that recurrent backers are the main transmission channel of cross-project funding dynamics: by initiating social learning about project existence and quality, recurrent backers encourage future funding by other backers. Our results demonstrate that even though contemporaneous projects compete for funding, they jointly benefit from their common presence on the platform. We finally show that these crowdfunding dynamics stir platform growth, with important consequences for competition among platforms.

JEL-Codes: D430, G230, L140, L260, L860.

Keywords: crowdfunding, digital platforms, FinTech, network effects, social learning.

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1. Introduction

Digital platforms represent an increasing share of the global economy and because they enter all sectors of activities, they pervade our everyday lives. The financial sector is no exception, with the emergence of FinTech platforms that offer nowadays a solid alternative to traditional financial institutions. Contrary to traditional firms, digital platforms do not control transactions but simply enable them. They create value by facilitating the interaction between different groups of users (Hagiu and Wright, 2015, 2019). It is therefore crucial for platforms to overcome the asymmetric information and coordination problems that arise among their users.

These problems are particularly pervasive on crowdfunding platforms (referred to hereafter as CFPs), whose role is to facilitate the interaction between entrepreneurs in need for funding and backers interested in financing projects. On the one hand, asymmetric information generates 'informational externalities': backers, being uncertain about project quality or existence, may try to infer information from the past decisions of other backers (giving rise to social learning).[1] On the other hand, coordination problems stem from the interdependence between the entrepreneurs' and backers' decisions on a CFP: the payoffs that any user may obtain (funding and visibility for entrepreneurs, some form of compensation for backers) heavily depend on other users' decisions; as a result, 'payoff externalities' (or network effects) prevail on CFPs.[2]

In this paper, we study how the interplay of social learning and network effects (i.e., of informational and payoff externalities) shape the performance and growth of CFPs. In particular, we are interested in 'crowdfunding dynamics', that is, the sequences of backers' funding decisions within a particular project and across different projects. To this end, we use a rich set of data from Ulule, one of the leading reward-based CFPs in Europe. Between 2010 and 2016 (our sample period), Ulule attracted more than 1.3 million backers on about 24 thousand entrepreneurial projects. To corroborate our analysis, we also use data from another large European CFP,

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[1] Bikhchandani, Hirshleifer, and Welch (1998, p. 153) define social learning as an "influence resulting from rational processing of information gained by observing others."

[2] 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.

KissKissBankBank (thereafter KKBB), which is the most direct competitor of Ulule on the French reward-based crowdfunding market.[3]

We derive three main sets of results from our empirical analysis. First, we provide a systematic assessment of crowdfunding dynamics. We show 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 'within-project funding dynamics', which have already been documented in the literature (e.g., Kuppuswamy and Bayus, 2017, 2018). We also show an entirely novel result, namely the existence of positive '*cross*-project funding dynamics': 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 fixed-effects estimator. 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 within-project funding dynamics) and approximately 0.5% higher following a 10% increase in the number of contributions in the other projects on a daily basis (i.e., cross-project funding dynamics). Our replication tests with KKBB data yield very similar economic effects.[4]

In order to establish more precisely the causal impact of cross-project funding dynamics, 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 cross-project funding dynamics surrounding fast starters' first campaign day. Our difference-in-differences estimates indicate that cross-project funding dynamics account for 4-5% increase in the number of contributions that a particular project obtains on a daily basis.

Our second set of results relates to a deeper explanation of the cross-project funding dynamics, obtained by contrasting the behavior of backers according to whether they contribute repeatedly ('recurrent backers') or just once ('new backers'). Our results show that recurrent backers act as the main transmission channel of cross-project funding dynamics. We provide evidence from

[3] Reward-based CFPs appear to be a superior setting than equity-based CFPs to identify social learning and 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.
[4] These results survive a battery of further robustness tests. They do not change significantly if we use alternative measures of within- and cross-project funding dynamics, if we exclude campaigns that already met their target goal, or if we resort to alternative econometric techniques.

Ulule, and also from KKBB, consistent with the idea that social learning is initiated by recurrent backers and contributes to mitigating information asymmetries about project existence or quality. First, we find that recurrent backers are more likely than new backers to contribute to successful projects, suggesting that recurrent backers are better at spotting successful projects. Second, we find that recurrent backers are more likely to contribute at earlier stages of the campaign than new backers, suggesting that they tend to back projects irrespective of other backers' decisions. These two findings explain why recurrent backers may exert a significant influence on later backers. Recurrent backers are instrumental in initiating social learning and generating positive network effects (more contributions to a given project increase the chances that this project will be financed and that backers will earn their reward). In sum, it is social learning coupled with positive network effects that explains how positive funding dynamics spill over from one project to another.

Our third set of results investigate the link between crowdfunding dynamics and platform growth. We compare the evolution in total number of contributions made by backers on both Ulule and KKBB platforms and uncover a widening gap of Ulule over KKBB. Then, we provide suggestive evidence that the widening gap we document relates to the number of recurrent backers growing at a faster pace on Ulule than on KKBB (33.1% *vs.* 3.0%).

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 cross-project funding dynamics), CFPs can increase total contributions by choosing the right mix of projects.[5] Another important lesson that CFP managers can draw from our work is that recurrent backers behave quite differently from new backers and, in particular, are recognized as 'social influencers'. We show indeed that projects having a higher fraction of recurrent backers appear to generate more contributions, suggesting that retaining existing backers yields larger returns than acquiring new backers.

[5] 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 'Heritage' and 'Art & Photo' categories are the ones that generate the largest synergies; the platform may then want to give more visibility to projects in these categories, as they are more conducive to stimulate platform growth.

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 learning and of 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 dominance. Our analysis suggests that a key variable explaining the growth path of CFPs is the share of recurrent backers that they manage to retain. This is what the widening gap between Ulule and KKBB—the two main competitors in the French crowdfunding market—suggests. 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 current policy debate about the dominance of BigTech platforms (Alibaba, Amazon, Facebook, Google, Tencent) and the way network effects serve as entry barriers in markets with platforms (BIS, 2019; Crémer, de Montjoye, and Schweitzer, 2019).

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.[6] For example, Kuppuswamy and Bayus (2017) study the dynamics of project contributions over time (i.e., 'within-project funding dynamics' in our parlance). The authors find that backers are more likely to pledge money on projects approaching their target goal. However, they remain silent about 'cross-project funding dynamics'. Furthermore, our novel entrepreneur-backer data on two competing reward-based CFPs in France allow us to assess how crowdfunding dynamics stir platform growth. Second, the literature on other forms of crowdfunding is also relevant for our work. In particular, the empirical research on marketplace lending reports informational externalities between lenders (see, e.g., Zhang and Liu, 2012), which are akin to the within-project funding dynamics that we document here. We build on this literature to show that the interplay with payoff externalities (i.e., network effects) is critical to fully apprehend both within- and cross-project funding dynamics. Finally, in this way, our paper gives additional empirical support to the

[6] 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), Mollick and Nanda (2016), Kuppuswamy and Bayus (2017), Strausz (2017), Cong and Xiao (2018), Viotto da Cruz (2018), Chemla and Tinn (2019), Cornelius and Gokpinar (2019), Cumming, Leboeuf, and Schwienbacher (2019), Kumar, Langberg, and Zvilichovsky (2019), Xu (2019).

theoretical literature on both informational and payoff externalities in digital economics (see, e.g., Drehmann, Oechssler, and Roider, 2005, and the references therein).

The rest of the paper runs as follows. Section 2 reviews the theoretical background and then derives testable hypotheses. Section 3 introduces Ulule and describes the data. Section 4 presents our empirical results. Section 5 concludes.

2. Theoretical Background and Hypotheses

2.1. Social learning and crowdfunding dynamics

After joining a CFP, backers face a set of complex decisions to make: 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. What makes these decisions complex is the lack of information. In particular, backers are usually not equipped to evaluate the quality of the projects nor the reliability of the entrepreneurs; and even if some backers may know more than others about some projects, their information remains private in the sense that other backers cannot easily observe it. In such a context, backers may try to infer information from other backers' decisions. In other words, information about project quality spreads through social learning (also known as 'informational externalities') during crowdfunding campaigns. There are also instances where it is rather information about the very existence of the project that spreads through social learning (Mobius and Rosenblat, 2014). For example, some backers get to know of a particular project and decide to contribute money to it. Their contributions may be observed by other backers and then diffuse by social contact across the CFP.

2.1.1. Within-project funding dynamics

The crowdfunding literature has largely studied the effects of social learning on the funding dynamics for a given project. The main question of interest is whether past contributions influence current ones. We can safely conjecture that the answer is yes: because backers have limited information about hidden quality of projects, they are likely to try and infer information from decisions made by previous backers. That is, past contributions do influence current ones, thereby generating 'within-project funding dynamics'. However, whether the influence of past contributions is positive or negative 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 within-project funding dynamics, as past backers attract new backers for a given project (Banerjee, 1992, Bikhchandani et al., 1992). Zhang and Liu (2012) provide evidence of herding (both rational and irrational) on the decisions of lenders on a marketplace lending platform.[7] Another reaction may be backers' eagerness to contribute to a project as it approaches its funding goal, that is, when they think that their impact is then the largest. This *goal-gradient effect* provides another source of positive within-project funding dynamics (Kuppuswamy and Bayus, 2017).[8] 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 within-project funding dynamics. From 577 Kickstarter projects, Li and Duan (2014) find the presence of the latter effect, alongside signs of herding behavior.

2.1.2. Cross-project funding dynamics

The different theoretical approaches reviewed above are useful to understand the dynamics of contributions within a given project, but how about dynamics *across projects*, that is, 'cross-project funding dynamics'? A quick extrapolation of our previous analysis would lead us to conclude that if within-project funding dynamics are positive, then cross-project funding dynamics should 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 rather restrictive 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. However, the total contributions on CFPs have been in continuous expansion over the last years and this trend shows

[7] See also Astebro et al. (2019) whose work examines whether equity-based crowdfunding campaigns are inducing investors to herd.

[8] 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. Prosocial motivations are invoked by Dai and Zhang (2019), who show that projects collect funding faster right before meeting their funding goals than right after (they use a dataset of 28,591 projects collected at 30-minute resolution from Kickstarter). Zvilichovsky, Danziger, and Steinhart (2018) study a related, but distinct, motivation for backers to feel pivotal. Using controlled experiments, the authors find that backers are motivated to make the product happen more than they are motivated to help the entrepreneurs.

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 within- and cross-project funding dynamics may well coexist, a hypothesis that (to our knowledge) has not been tested so far. As we just hinted, a theoretical explanation for the existence of positive cross-project funding dynamics is the expansion of the total contributions due to social learning. Positive cross-project funding dynamics may come from information about project existence and quality that diffuses between (heterogeneous) backers across the CFP. Backers are likely to differ according to their familiarity with a given CFP. In particular, 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 evaluate projects, how to follow campaigns, etc. Recurrent backers are likely to make more informed decisions than new backers. More information can thus be inferred from observing the behavior of more experienced decision-makers (see Vismara, 2016, on equity-based CFP, and Kim and Viwanathan, 2019, on CFP for mobile applications). Recurrent backers thus generate social learning through their decisions to back sequentially different projects (either in the same or in different categories). By doing so, recurrent backers are potentially an important source of cross-project funding dynamics.

Another theoretical explanation behind positive cross-project funding dynamics is the expansion of the total contributions on a given CFP due to network effects: the value that each user can derive from the CFP depends on the combined decisions of all the other users of the CFP (Belleflamme and Peitz, 2018). Network effects, discussed now, are also known as 'payoff externalities' insofar as the payoff that any user may obtain (funding and visibility for entrepreneurs, some form of compensation for backers) is affected by the decisions of other users.

2.2. Network effects and crowdfunding dynamics

As two-sided platforms, CFPs enable the interaction between two 'sides' (here, backers and entrepreneurs) whose needs require coordination. As a result, a CFP becomes more attractive for the users in one group as participation increases in the other group. 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 (Belleflamme, Omrani, and Peitz, 2015). 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.[9] One talks here of *indirect* network effects: backers enjoy the presence of other backers, not directly but indirectly through the increased presence of entrepreneurs, which in turn benefits backers; the same applies for entrepreneurs.

There also exist *direct* network effects on CFPs, insofar as participation decisions by one user in a particular group affect directly the other participants in this user's own group. The impact of these network effects within the group of backers is a priori ambiguous (Belleflamme et al., 2015).[10] Increased backer participation implies increased availability of funds overall, which makes it more likely that more projects are funded and, hence, more rewards are earned: a positive direct network effect.[11] 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.[12]

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 users a CFP attracts, the larger its market share in the crowdfunding market and the more attention it will receive in the media and in social networks,

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[9] We only know of one empirical study documenting such network effects on a CFP, namely Thies, Wessel, and Benlian (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 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.

[10] Similarly, network effects within the group of entrepreneurs also apply. Since we do not have any information to study them, we need not discuss them in more detail (see Belleflamme et al., 2015, for further developments in the crowdfunding context, and Koh and Fichman, 2014, for empirical evidence from online business-to-business exchanges).

[11] This effect is amplified when the first backers attract subsequent backers either through direct solicitations or through word-of-mouth. Smith, Windmeijer, and Wright (2015) show the existence of such positive direct network effects in charitable giving.

[12] Negative direct network effects may also exist across different types of backers. 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 direct network effect on the producers of high-quality apps on both Apple and Google app stores.

which contributes to attract even more users. Second, by managing more users 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.[13]

In sum, the interaction among backers, and between backers and entrepreneurs, generate various sorts of informational externalities (stemming from social learning) and payoff externalities (stemming from network effects).[14] These two types of externalities shape crowdfunding dynamics and platform growth in complementary ways: network effects contribute to attract new contributions across the board, while social learning affects these new contributions that are allocated across projects (following the choices made initially by recurrent backers); also, network effects continue to reinforce crowdfunding dynamics even after social learning has ceased (i.e., once backers have gained full information about project existence or quality).

2.3. Testable hypotheses

We now draw three testable hypotheses from the above theoretical analysis. First, we conjecture that social learning and positive direct network effects among backers generate *positive within-project funding dynamics*:

Hypothesis 1. Current contributions to a given project increase with past contributions to that project.

Second, we expect that social learning and positive network effects raise the opportunity of *positive cross-project funding dynamics:*

Hypothesis 2. Current contributions to a given project increase with past contributions to *other* projects.

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[13] 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).

[14] An open question remains as to how information and payoff externalities interact. The theoretical literature usually examines the two sources of externalities separately (models of social learning assume that individual payoffs are independent of other players' actions, while models of network effects are mostly static and assume complete information). Only a handful of papers integrate the two sources, in different ways and with ambiguous results (see, e.g, Arieli, 2017).

Note that we can refine Hypotheses 2 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 cross-project funding dynamics is then evaluated for the contributions to the other projects belonging to the same category or to different categories.

As mentioned above, both within- and cross-project funding dynamics could arise even absent social learning. This is especially true at the beginning of the crowdfunding phenomenon, where the increasing interest in crowdfunding spurred growth of platforms and thereby generated network effects. To see whether social learning is also at play, we therefore need a finer set of hypotheses that are unique to social learning. Our discussion on social learning posits that recurrent backers play a key role behind the emergence of distinct, positive cross-project dynamics by initiating learning by new backers. To substantiate this theory, we test whether recurrent backers are, concomitantly, less influenced by and more influential for other backers’ decisions.

Hypothesis 3a. Recurrent backers are more likely to contribute to projects ending successfully.

Hypothesis 3b. Recurrent backers contribute earlier to projects than other backers.

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 June 2019, Ulule attracted more than 2.5 million registered members and facilitated the financing of over 28,000 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[15] 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

[15] Financial rewards are not allowed.

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.

Table 1 provides summary statistics for the universe of Ulule projects. The first set of variables measures the various project dynamics 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 9.7). In terms of volume, the average daily amount of contributions is about €80, with a median of €5 and a standard deviation of €512. As for the number of the other category-wide (platform-wide) contributions, the average is approximately 97 (837) and the standard deviation is 104 (552). 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 45%. 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).

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]

We will also test the robustness of our results using data on the universe of projects listed on KKBB (www.kisskissbankbank.com), a large reward-based CFP in France using an AoN scheme. Since KKBB inception in September 2009, about 1.7 million backers contributed to more than 35,000 listed projects, out of which 20,500 were successfully funded. With a similar platform design and geographical scope, KKBB is the main competitor of Ulule. We will further discuss KKBB when conducting our robustness tests.

4. Empirical Analysis

4.1. Crowdfunding dynamics

To study crowdfunding dynamics (i.e., within- and-cross project funding dynamics), we estimate the following specification:

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

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_{it}, 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.[16] $Y_{i,t-1}$ is the number of backers' contributions that project i has received by the end of day $t-1$ (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). $\boldsymbol{X}_{it}$ is a vector of control variables and ε_{it} is the error term.[17] The vector of control variables takes into account time-varying project-level characteristics (namely, # projects, % goal, Popular, which are defined in table notes). The coefficient of interest, β_1, measures within-project funding dynamics on the number of contributions received by a particular project, while the coefficients of interests, β_2 and β_3, measure cross-project funding dynamics. 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.[18]

Table 4 reports the coefficients of fixed-effect regression models derived from specification 1. We first estimate within- and cross-project funding dynamics separately. In column 1, we estimate within-project funding dynamics 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 cross-project funding dynamics instead. Column 2 estimates cross-project funding dynamics within categories, while column 3 describes cross-project funding dynamics across categories. The coefficients of interests, β_2 and β_3, are both positive and significant at the 1% level. Next, in column 4, we estimate the same specification, but we consider within- and cross-project funding

[16] 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.

[17] 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 in footnote 19.

[18] 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. However, in section 4.2 we test the robustness of our results by using the rolling average of past contributions over various time windows.

dynamics together. The results are unchanged: β_1, β_2, and β_3 are positive and significant. Since the contributions made are highly conditional on current funding status (Mollick, 2014; Strauzs, 2017), in column 5 we restrict our sample to the campaign period during which the funding goal of projects is not (yet) met. In column 6, we go on by investigating the differential funding dynamics across each of the 15 Ulule categories. Again, the estimates of the coefficients of interest are positive and significant.[19]

Across columns 1-6, the coefficients of within- and cross-project funding dynamics are positive, always statistically significant at the 1% level, and have similar magnitudes. The respective contributions of within- and cross-project dynamics have large economic consequences. Using results from column 4, a 10% increase in the number of contributions on project *i* results in a 2.07% increase in the number of contributions the day after on the same project *i* while holding all other variables constant.[20] This result confirms the findings of prior works (cited in section 2.1.1) documenting within-project funding dynamics in a similar way. However, the novelty here is the identification of sizeable cross-project funding dynamics. 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 0.15% (0.52%) increase in the number of contributions on a project.[21] The results on cross-project funding dynamics from column 5, focusing on campaign periods in which projects are not fully funded, yield slightly higher economic magnitudes. Furthermore, the results from column 6 indicate that some categories generate relatively more cross-project funding dynamics than other categories. For example, the categories 'Heritage' and 'Art & Photo', with large and significant coefficients, exhibit more pronounced cross-project funding dynamics 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 Ulule:

[19] The 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. Consistent with our expectations that the fixed-effects estimator has at most a small bias, our GMM estimates (unreported) are similar to the ones reported in Table 4.

[20] Recalling that we have a log-log model, this implies that a 10% increase in $Y_{i,t-1}$ multiplies y_{it} by $e^{0.215*\ln(1.1)} \approx 1.0207$.

[21] That is, a 10% increase in $Y_{-i,t-1}$ multiplies y_{it} by $e^{0.016*\ln(1.1)} \approx 1.0015$, and a 10% increase in $Y_{-j,t-1}$ multiplies y_{it} by $e^{0.054*\ln(1.1)} \approx 1.0052$.

by attracting a crowd of specialized backers, this category does generate cross-project funding dynamics but only within the category itself.

The evidence from control variables throughout the specifications of Table 4 shows that the number of active projects within categories negatively impacts the number of contributions received. 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 by projects increases as the campaign is approaching its funding goal, consistent with the goal-gradient effect documented by Kuppuswamy and Bayus (2017). Projects being part of the ones featured on the first page of Ulule appear to generate more contributions.

[Insert Table 4 about here]

Collectively, these results, supporting Hypotheses 1 and 2, strongly characterize the importance of both within- and cross-project funding dynamics in CFPs. We now turn to evaluate the robustness of these main results.

4.2. *Robustness tests*

Tables A1 and A2 probe the robustness of our results to alternative definitions of the variables of interest.[22] We first 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 crowdfunding dynamics 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 funding dynamics only affecting either small-sized contributions or large-sized contributions. In Panel A of Table A1, we mirror the specifications of columns 1-6 in Table 4 for the variables of interest in €-amount. Considering the volume of contributions does not change our prior conclusions, neither statistically nor economically.

Another potential concern is that the high (daily) frequency used to identify crowdfunding dynamics may capture short-term liquidity fluctuations rather than category-wide (platform-wide) dynamics. To assuage this concern, we re-estimate within- and cross-project funding dynamics

[22] To conserve space, all the tests in this section are relegated to the appendix.

using the rolling average of past contributions over different time windows instead of the contributions of the past day. Table A2 mirrors the specification of column 4 in Table 4 using the rolling average over a 3-day (column 1), 5-day (column 2), 7-day (column 3), and 10-day (column 4) window, respectively. Our conclusions are unchanged.

Last, in Table A3 we test the replicability of our results using data from a different platform which uses an AoN reward-based scheme: KKBB. We obtained from KKBB similar granular data than from Ulule, which also allow us to trace the exact timing and amount pledged by all backers over the period between May, 23 2010 and December 31, 2015. The only difference is that KKBB categories have been redefined several times during the period of investigation, in turn affecting the clean identification of cross-project funding dynamics. Therefore, we prefer to estimate, unlike in the Ulule analysis, cross-project funding dynamics without differentiating between cross-project funding dynamics within categories *and* across categories.[23] In Panel A of Table A3, we estimate within- and cross-project funding dynamics separately (columns 1 and 2) and together (column 3).[24] As can be seen, the coefficients of within- and cross-project funding dynamics are positive, always statistically significant at the 1% level, except in column 3 where the coefficient of cross-project funding dynamics turns out to be insignificant. Regarding the economic significance of the results, we find that a 10% increase in the number of contributions within (across) projects on a particular day subsequently leads to a 2.26% (0.11%) increase in the number of contributions on a project (using the results from columns 1 and 2). Economically, these results on KKBB platform are very similar to the results on Ulule platform.

4.3. Identifying cross-project funding dynamics around fast starts

The systematic examination of crowdfunding dynamics in the previous sections revealed the existence of large *cross-project* funding dynamics, which deserve further attention. In this section, we sharpen the identification of cross-project funding dynamics using plausibly exogenous variation from 'fast starters'. This allows us to test Hypothesis 2 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

[23] Note, however, that differentiating between cross-project funding dynamics within categories and across categories by creating coherent categories does not change qualitatively the results presented in Table A3.
[24] Panel B of Table A3 reports summary statistics for the variables used.

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.[25] Then, we employ a difference-in-differences framework to estimate cross-project funding dynamics.[26] Specifically, we estimate the following model:

$$y_{ijt} = \alpha_i + \alpha_t + \beta Fast\ start_{jt} + \boldsymbol{\gamma} \boldsymbol{X}_{it} + \varepsilon_{ijt}, \quad (2)$$

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

[Insert Table 5 about here]

This analysis presented in Table 5 yields two main results that confirm Hypothesis 2. First, we find that when a project experiences a fast start, the other contemporaneous projects benefit from it. Specifically, in odd-numbered columns of Table 5, we estimate the cross-project funding dynamics generated on the CFP by fast starters.[27] We find that the coefficient of interest is always positive and significant at the 1% level. Fast starters are not included in the sample to make sure that our coefficient estimates are not contaminated by the fast starters themselves. When a project on the CFP attracts more than 200 contributions on that day, it leads to a 1.51% increase in the number of daily contributions a particular project gets (i.e., by a multiple of $e^{0.015} = 1.0151$, based on column 1 estimations). This effect is stronger the higher the number of contributions the fast starter generates: 2.94% increase if it gets more than 500 contributions (column 3). Second, we find that the impact of fast starters is more pronounced on projects within their own category

[25] Table A4 reports the outcome of our search on Factiva.

[26] 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 cross-project dynamics. That is, one would have to find an unobserved contemporaneous change that systematically accompanies fast starters across the platform and over time.

[27] In other words, we estimate a single time-series difference by comparing the outcome after the fast start with the outcome before the fast start.

(i.e., β in specification 2). In even-numbered columns, we present the difference-in-differences estimates of the effect of fast starters. When a project unexpectedly generates more than 200 contributions in its first day, it implies a 4.08% increase in the number of daily contributions received by the other projects within the same category, while it leads to a 1.41% increase for projects outside the category (using estimates from column 2). Again, these effects are stronger when fast starters generate more than 500 contributions (see column 4).[28]

4.4. New backers vs. *recurrent backers*

So far, we considered backers as a homogenous group of individuals, irrespective of them being new or recurrent on the CFP. As mentioned before, recurrent backers are likely to generate informational externalities on other backers. As a prequel to our analysis on the transmission channel of crowdfunding dynamics, we now investigate whether different groups of backers (i.e., new *vs.* recurrent) affect within- and cross-project dynamics differently.

Table 6 displays the results. In Panel A, we estimate within- and cross-project funding dynamics similarly than in Table 4, except that we differentiate past contributions by new backers from past contributions by recurrent backers. On Ulule, backers do indeed observe whether previous backers are recurrent or not. In columns 1 to 3, we look at within- and cross-project funding dynamics separately, while in column 4 we examine them together.[29] The results across columns 1-4 show that both new and recurrent backers drive within- and cross-project effects, with positive coefficients statistically significant at the 1% level in most cases. The significance level of the Wald test (reported in brackets) is close to zero; we can thus reject the hypothesis of no differences between new backers and recurrent backers. New and recurrent backers thus produce distinct effects on funding dynamics.

In Panel B, we estimate cross-project funding dynamics surrounding fast starts, except that we differentiate between fast starters attracting relatively more contributions from recurrent backers than from new backers during their first day, and vice versa. Our difference-in-differences estimates (reported in columns 2 and 4) depict a clear pattern: fast starters counting relatively more contributions from recurrent backers than from new backers generate significantly higher cross-

[28] These results are qualitatively the same if one uses the volume of contributions (in €-amount) instead of the number of contributions as variables of interest (see Panel A of Table A5).

[29] Our results (unreported) restricting the sample to the campaign period of projects when the target goal is not yet reached are in line with the results on the full sample reported in Table 6.

project effects than fast starters having attracted more new backers than recurrent backers. The statistical significance only persists for 'recurrent fast starters', which lead to a 7.68% and 2.33% increase in the number of daily contributions generated by projects, respectively, within their category and outside their category (using estimates from column 2).

Moreover, we verify the robustness of our results in this section using instead the €-amount of contributions as dependent variables of interest (see Panel B of Tables A1 and A5, respectively). We do not find any evidence that alters our conclusions on recurrent backers. The results in this section suggest that recurrent backers play a distinct role than new backers in shaping within- and cross-project funding dynamics. We explain their role in the next section.

[Insert Table 6 about here]

4.5. The role of recurrent backers

In this section, we document the main transmission channel of within- and cross-project funding dynamics. We provide two sets of regression analysis that aim at understanding the extent to which recurrent backers' behavior is less dependent on social influences. Specifically, we study what projects recurrent backers contribute to and when they contribute to them. The first analysis tests whether recurrent backers are more likely to contribute to successful projects. The second analysis tests whether recurrent backers contribute at earlier stages of the campaign than other backers.

To study social learning initiated by recurrent backers, we collapse our dataset at the individual contribution level and perform linear regressions of the following specification:

$$y_{ik} = \alpha + \beta_1 X_{ik} + \beta_2 X_{-ik} + \beta_3 X_{-jk} + \boldsymbol{\gamma} \boldsymbol{X}_{ijk} + \varepsilon_{ik}. \tag{3}$$

Here y_{ik} is one of our two measures of individual learning: $Success_{ik}$ and $Timing_{ik}$; $Success_{ik}$ takes the value of one if backers' contribution k is made on a project i that will eventually end up being successful (zero otherwise), and $Timing_{ik}$ is the day of the campaign when backers' contribution k is made to project i divided by the campaign duration in days. α is a constant term, X_{ik} takes the value of one if the contribution k is made by a backer recurrent within project i (zero otherwise), X_{-ik} takes the value of one if the contribution k is made by a backer recurrent within the same category of project i (zero otherwise), and X_{-jk} takes the value of one if the contribution k is made by a backer recurrent in any other categories j except the category of project i (zero otherwise). The vector $\boldsymbol{X}_{ijk}$ contains a variety of factors, controlling for backer's age, backer's first project €-amount pledged, campaign duration, project size, entrepreneur experience, cash contribution, backer's country of residence fixed effects, category fixed effects, and day fixed effects; ε_{ijk} denotes the error term. The coefficients of interest, β_1, β_2, and β_3, measure the propensity of recurrent backers (respectively, within project i, within category $-i$, and across categories $-j$) to contribute either to successful projects or earlier relative to new backers (captured in the constant term). Statistical inference is based on heteroskedasticity-robust standard errors clustered at the backer level.[30]

Tables 7 and 8 report our estimates of equation 3.[31] The results across columns 1-7 of Table 7 show clear support for Hypothesis 3a. We first estimate the effect of recurrent backers within project i (column 1), within category $-i$ (column 2), and across categories $-j$ (column 3) on project success separately and then together (column 4). The full set of control variables and fixed effects is included in all specifications. The coefficients of interest are always positive and statistically significant at conventional levels, meaning that recurrent backers are more likely than new backers (captured in the constant term) to contribute to successful projects. Using estimates from column 4, the probability of contributing to successful projects increases by 2.8 percentage points (pp) for backers having already contributed to the project, while this increased probability is of 0.3 pp (1.5 pp) for backers who previously contributed to project(s) within the same category (to project(s) in any other categories). In column 5, we look at the success ratio as an alternative dependent variable of interest. Consistent with the results on project success, we find that backers increase the success ratio by 7.8 pp (8.2 pp) if they previously contributed to other projects within the same category (in other category) than project i. In the remaining columns, we replicate the specification of columns 4 and 5 using contributions made on the KKBB platform. The estimation results are qualitatively similar. Taken together, these results suggest that recurrent backers, through their past experience on the CFP, are better at spotting projects that may be successful.

Then, the results from Table 8 confirm Hypothesis 3b. In columns 1 to 3, we estimate the effect of recurrent backers within category $-i$ and across categories $-j$ on funding cycle timing. The

[30] It is important to note that all our results survive if we cluster the standard errors at the project level rather than at the backer level. These results can be obtained upon request.
[31] Given the dense set of fixed effects used, we prefer to use OLS models. However, average marginal effects of Probit models are very similar.

specifications are the same as before, except that we do not estimate here the effect of recurrent backers within project *i* because of the tautological relationship between subsequent contributions and funding cycle timing. We find that the coefficients on 'within category' recurrent backers are negative and statistically significant at the 1% level (here 'negative' means earlier timing). The coefficients obtained on 'other category' recurrent backers also appear negative and statistically significant at conventional levels. The magnitude of the 'within category' effects is meaningful. Using the result from column 3, recurrent backers having already contributed to a project within the same category are 2.5% more likely to contribute to projects before new backers (the sample mean is 45.7%). To give an economic sense, recurrent backers are likely to contribute, on average, one day before new backers (assuming an average campaign duration of 36 days). Finally, in column 4, we replicate the specification of column 3 using contributions from KKBB. The results, always statistically significant at the 1% level, are very consistent and provide additional support to Hypothesis 3b.

[Insert Tables 7 and 8 about here]

Summing up, the results in this section suggest that recurrent backers make decisions that are less dependent on social influence, as they are relatively more likely to contribute (1) to successful projects and (2) before new backers. Through their more independent decisions, recurrent backers act as an important transmission channel of crowdfunding dynamics, which give rise to social learning. Importantly, this is the case regardless backers are recurrent within a project or across the platform, meaning that they play a learning role in the emergence of both within- and cross-project funding dynamics. We now discuss the link between crowdfunding dynamics and platform growth.

4.6. Social learning, network effects, and platform growth

Recurrent backers, by initiating social learning, drive crowdfunding dynamics. Social learning by new backers has indeed the likely consequence of overcoming asymmetric information problems that relate to project existence or quality. To what extent does the behavior of recurrent backers reverberate at the platform level? In particular, do recurrent backers contribute to amplify the total numbers of contributions generated over time?

To provide insight to this question, we describe the evolution of the share of recurrent backers on both Ulule and KKBB platforms. Figure 1 exhibits the total monthly number of contributions made by project backers on Ulule (top graph) and KKBB (bottom graph) platforms from their inception onwards. Both platforms experienced a clear rise in the number of contributions over time, with the bulk of these contributions being made by new backers (blue line). The number of recurrent backers (red line) also increases over the period under investigation, though at different pace across both platforms. Ulule has a significantly higher share of recurrent backers than KKBB.[32] A closer look at these differences between both CPFs confirms this pattern. Table 9 presents statistics on daily contributions made by recurrent backers per project across categories in Ulule (Panel A) and KKBB (Panel B), respectively. Recall that both CFPs were launched around the same period. As can be seen, the number of recurrent backers per project starts on average by being of similar order of magnitude in 2010 in both platforms and, then, increases significantly more on Ulule than KKBB over the years (the compound annual growth rate over the sample period is 33.1% and 3.0% for Ulule and KKBB, respectively). In contrast to Ulule, KKBB even shows negative growth in the number of recurrent backers in the recent period. Moreover, we note interesting variations across categories in both CFPs, typically with categories like 'Publishing & Journalism' having an increasingly higher number of recurrent backers. Next, Figure 2 exhibits the evolution of the difference in the total number of contributions between both CFPs. The figure clearly shows a widening gap between Ulule and KKBB, its most direct competitor. This gap is especially marked in the most recent year. Taken together, Figures 1 and 2 suggest that recurrent backers partly account for the diverging growth trajectories of Ulule and KKBB. This also means that Ulule would have better succeeded at retaining recurrent backers since its inception.

[Insert Figures 1 and 2 and Table 9 about here]

Although the role of recurrent backers at initiating social learning provides a compelling reason explaining the growth of Ulule and KKBB, other forms of externalities may also be at work. Indeed, the number of contributions may further increase as network effects kick in (see section 2.2). In particular, some backers are incentivized to contribute to a given project if other backers contribute as well. This mechanism may arise even when all backers have full information about the existence or quality of the project. Network effects are unlikely to wear off, especially before campaigns reach their target goal and can therefore amplify crowdfunding dynamics after any hidden information about projects would have been learned. The growth path of CFPs rather

[32] The proportion of recurrent contributions over the sample period is on average 12.7% for Ulule projects *vs*. 6.8% for KKBB projects (untabulated statistics).

depends on the interaction between network effects and social learning.[33] This has important implications for competition among CFPs as both learning and network effects create positive feedback loops, which tend to make strong CFPs stronger and weak CFPs weaker. Our evidence on the diverging growth trajectories of Ulule and KKBB, at least, suggests so.

5. Conclusion

This study adds to the literature on FinTech and, in particular, crowdfunding by providing empirical estimates of the extent of funding dynamics within and across projects. By analyzing various sorts of social learning and network effects in two leading European CFPs, our findings inform about the most fundamental determinants of both the rise of FinTech 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 both learning and network effects on funding 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 or token-based platforms.

The richness of our data shows that social learning and network effects conflate in a complex way and have large economic impacts on the performance and growth of platforms. First, using unique data from two prominent French reward-based CFPs, Ulule and KKBB, we document the intensity of crowdfunding dynamics. Besides the meaningful role of within-project dynamics already documented in prior work, our evidence uncovers that cross-project dynamics are non-negligible: they imply a 4 to 5% increase in the daily project contributions. Second, recurrent backers play a significant role in shaping these crowdfunding dynamics. We find that recurrent backers tend to contribute earlier than other backers and more to successful projects. This evidence suggests that other backers learn from recurrent backers' pledge decisions, reducing their lack of information about project existence and quality. Third, we provide evidence that the evolution of the number

[33] Since we do not have any information to further disentangle the various sorts of learning and network effects, we leave, however, for future research the empirical assessment of their relative intensity.

of recurrent backers plausibly accounts for diverging growth trajectories of both Ulule and KKBB platforms in the past decade. Bottom line: recurrent backers, by driving crowdfunding dynamics, represent a fundamental source of the growth of CFPs.

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Table A1. Within- and cross-project funding dynamics: €-value of contributions

This table presents fixed-effects estimates of the within and cross-project funding dynamics 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 within-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 cross-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 cross-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 being featured on the first page of Ulule website during a day and 0 otherwise. Columns 1-4 and 6 of Panel A include all observations from all projects, while column 5 excludes the observations of projects when their target goal is reached. In Panel B, estimation results differentiate new backers and recurrent backers for each independent variable of interest as in Table 6 ('recurrent' means backers having previously contributed at least once either in the project, or in any other projects of the same category, or in any other projects of any other categories). The sample contains all projects posted on the Ulule platform between 5 July 2010 and 29 November 2016. *p*-values [in brackets] are from Wald tests assessing the statistical significance of differences between select coefficients. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by project. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: All backers

	(1)	(2)	(3)	(4)	(5)	(6)
€-value contributions$_{i,t-1}$	0.141***			0.140***	0.104***	0.139***
	(0.002)			(0.002)	(0.002)	(0.002)
€-value contributions$_{-i,t}$		0.038***		0.026***	0.026***	
		(0.004)		(0.003)	(0.004)	
€-value contributions$_{-j,t}$			0.160***	0.116***	0.119***	
			(0.008)	(0.008)	(0.008)	
€-value contributions$_{\text{Art \&Photo},t-1}$						0.022***
						(0.003)
€-value contributions$_{\text{Charities \& Citizen},t-1}$						0.027***
						(0.004)
€-value contributions$_{\text{Childhood \& Education},t-1}$						0.008***
						(0.002)
€-value contributions$_{\text{Comics},t-1}$						0.009***
						(0.003)
€-value contributions$_{\text{Crafts \& Food},t-1}$						0.012***
						(0.003)
€-value contributions$_{\text{Fashion \& Design},t-1}$						0.002
						(0.002)
€-value contributions$_{\text{Film \& Video},t-1}$						0.015***
						(0.004)
€-value contributions$_{\text{Games},t-1}$						0.005**
						(0.002)
€-value contributions$_{\text{Heritage},t-1}$						0.007***
						(0.002)
€-value contributions$_{\text{Music},t-1}$						0.027***
						(0.004)
€-value contributions$_{\text{Other},t-1}$						0.008***
						(0.002)
€-value contributions$_{\text{Publishing \& Journalism},t-1}$						0.014***
						(0.003)
€-value contributions$_{\text{Sports},t-1}$						0.011***
						(0.003)

€-value contributions$_{Stage,t-1}$						0.027***
						(0.003)
€-value contributions$_{Technology,t-1}$						0.005***
						(0.002)
# projects$_{i,t}$	0.029	-0.023	-0.021	-0.048*	-0.021	-0.058**
	(0.025)	(0.029)	(0.029)	(0.026)	(0.028)	(0.026)
% goal$_{t-1}$	-0.550***	-0.341***	-0.343***	-0.551***	-0.562***	-0.553***
	(0.019)	(0.021)	(0.021)	(0.019)	(0.027)	(0.019)
Popular$_t$	2.381***	2.516***	2.520***	2.385***	2.352***	2.388***
	(0.022)	(0.023)	(0.023)	(0.022)	(0.026)	(0.022)
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	681,740	814,951
# projects	23,022	23,022	23,022	23,022	22760	23,022
R^2	0.345	0.333	0.333	0.346	0.349	0.346

Panel B: Recurrent backers vs. new backers

	(1)	(2)	(3)	(4)
€-value new contributions$_{i,t-1}$ [1]	0.128***			0.127***
	(0.002)			(0.002)
€-value recurrent contributions$_{i,t-1}$ [2]	0.097***			0.096***
	(0.002)			(0.002)
€-value new contributions$_{-i,t-1}$ [1]		0.033***		0.022***
		(0.004)		(0.003)
€-value recurrent contributions$_{-i,t-1}$ [2]		0.010***		0.005**
		(0.002)		(0.002)
€-value new contributions$_{-j,t-1}$ [1]			0.160***	0.114***
			(0.009)	(0.009)
€-value recurrent contributions$_{-j,t-1}$ [2]			0.025***	0.016***
			(0.004)	(0.004)
p-value [1] = [2]	[0.000]	[0.000]	[0.000]	-
Control variables	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes
# observations	814,960	814,960	814,960	814,960
# projects	23,022	23,022	23,022	23,022
R^2	0.348	0.333	0.333	0.348

Table A2. Within- and cross-project funding dynamics: Rolling average of past contributions

This table presents fixed-effects estimates of the within- and cross-project funding dynamics (using alternative variable definitions) 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). # $contributions_{i,t-1}$ is the rolling average of past contributions over various time windows (3-day, 5-day, 7-day, and 10-day, respectively) and captures within-project dynamics. # $contributions_{-i}$ is the rolling average of past contributions received by projects referenced in the same category of project *i* during the indicated time window except the project *i* itself (in log) and captures cross-project dynamics within categories. # $contributions_{-j}$ is the rolling average of past contributions received by projects referenced in all other categories during the indicated time window except the category of project *i* itself (in log) and captures cross-project dynamics across categories. Control variables include # $projects_i$, % goal, Popular. # $projects_i$ is the number of projects within category *i* (in log). % goal is the ratio of the amount raised to targeted goal, Popular is a dummy variable equal to 1 if the project is among the 8 projects being featured on the first page of Ulule website during a day and 0 otherwise. 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.

	3-day window	5-day window	7-day window	10-day window
	(1)	(2)	(3)	(4)
# $contributions_{i,[t-1;t-3]}$	0.317***			
	(0.003)			
# $contributions_{-i,[t-1;t-3]}$	0.012***			
	(0.002)			
# $contributions_{-j,[t-1;t-3]}$	0.039***			
	(0.003)			
# $contributions_{i,[t-1;t-5]}$		0.350***		
		(0.003)		
# $contributions_{-i,[t-1;t-5]}$		0.008***		
		(0.003)		
# $contributions_{-j,[t-1;t-5]}$		0.026***		
		(0.004)		
# $contributions_{i,[t-1;t-7]}$			0.369***	
			(0.003)	
# $contributions_{-i,[t-1;t-7]}$			0.007**	
			(0.003)	
# $contributions_{-j,[t-1;t-7]}$			0.020***	
			(0.004)	
# $contributions_{i,[t-1;t-10]}$				0.361***
				(0.004)
# $contributions_{-i,[t-1;t-10]}$				0.005*
				(0.003)
# $contributions_{-j,[t-1;t-10]}$				0.023***
				(0.005)
Control variables	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes
# observations	814,960	814,960	681,740	814,960
# projects	23,022	23,022	22,760	23,022
R^2	0.468	0.468	0.468	0.469

Table A3. Within- and cross-project funding dynamics: KKBB platform

This table presents fixed-effects estimates of the within- and cross-project funding dynamics 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). The lag of the dependent variable captures within-project dynamics. # contributions_j is the number of contributions received by projects referenced in all categories of the platform during a day except the project *i* itself (in log) and captures cross-project dynamics. 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 12 projects being featured on the first page of KKBB website during a day and 0 otherwise. Unlike in columns 1 to 3 of Panel A, estimation results in columns 4 to 6 differentiate new backers and recurrent backers for each independent variable of interest, like in Table 6 ('recurrent' means backers having previously contributed at least once either in the project, or in any other projects of the platform). Panel B presents summary statistics for the variables used in Panel A. The sample contains all contributions made on the KKBB platform between 23 May 2010 and 31 December 2015. 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: Regression results

	(1)	(2)	(3)	(4)	(5)	(6)
# $\text{contributions}_{i,t-1}$	0.234***		0.234***			
	(0.002)		(0.002)			
# $\text{contributions}_{j,t-1}$		0.012***	0.002			
		(0.004)	(0.003)			
# new $\text{contributions}_{i,t-1}$ [1]				0.210***		0.210***
				(0.002)		(0.002)
# recurrent $\text{contributions}_{i,t-1}$ [2]				0.153***		0.154***
				(0.003)		(0.003)
# new $\text{contributions}_{j,t-1}$ [1]					-0.014***	-0.018***
					(0.003)	(0.003)
# recurrent $\text{contributions}_{j,t-1}$ [2]					0.033***	0.012***
					(0.005)	(0.004)
p-value [1] = [2]				[0.000]	[0.000]	-
Control variables	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	560,209	560,209	560,209	560,209	560,209	560,209
# projects	13,966	13,966	13,966	13,966	13,966	13,966
R^2	0.459	0.433	0.459	0.460	0.433	0.460

Panel B: Summary statistics

Variable	Mean	Std dev	Median	Min	Max	# obs
Variables of interest						
# contributions_i	1.110	5.419	0.000	0.000	1,773.000	576,738
# contributions_j	592.732	319.671	574.000	0.000	2,592.000	576,738
Control variables						
# projects_i	65.407	61.160	50.000	1.000	1,859.000	576,738
% goal	0.147	0.168	0.065	0.001	0.600	576,738
Popular	0.039	0.194	0.000	0.000	1.000	576,738

Table A4. 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 two 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	Prior to campaign launch
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
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 A5. Cross-project funding dynamics 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 equal to 1 during a day a project counts more than 200 (or 500) contributions in its first campaign day and 0 otherwise. Similarly, Fast start$_{j(-j)t}$ is a dummy variable equal to 1 during a day a project counts more than 200 (or 500) contributions in its first campaign day within a category *j* (in other categories *-j*). These dummy variables capture the cross-project dynamics of a project's fast start (within and/or across categories). Appendix Table A4 reports the projects that experienced an unexpected fast start. Unlike in Panel A, the 'Fast start' dummy variables in Panel B differentiate of whether the contributions in the first campaign day are made by new backers or by recurrent backers as in Table 6 ('recurrent' means backers having previously contributed at least once in the category *j(-j)*). Control variables included in the estimations but unreported for brevity are €-value contributions$_{i,t-1}$, # projects$_i$, % goal, Popular and are defined as in Table 4. The sample contains all projects (except the fast starters themselves) 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 backers

	>200		>500	
	(1)	(2)	(3)	(4)
Fast start$_t$	0.030*		0.080***	
	(0.015)		(0.026)	
Fast start$_{jt}$ [1]		0.092*		0.086
		(0.054)		(0.077)
Fast start$_{-jt}$ [2]		0.025		0.079***
		(0.016)		(0.027)
p-value [1] = [2]		[0.2339]		[0.9285]
Controls	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes
# observations	813,983	813,983	814,585	814,585
# projects	22,995	22,995	23,011	23,011
R^2	0.329	0.329	0.331	0.331

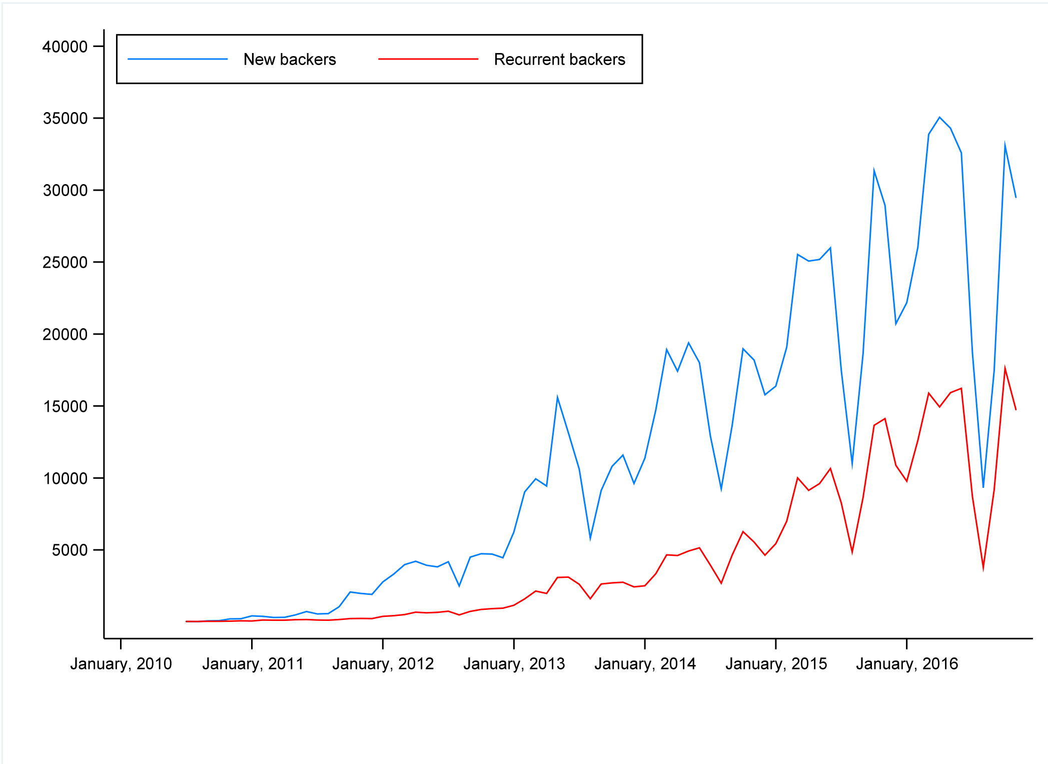
Panel B: Recurrent backers vs. new backers

	>200		>500	
	(1)	(2)	(3)	(4)
'New' Fast start$_t$	-0.041		-0.056	
	(0.025)		(0.049)	
'New' Fast start$_{jt}$ [1]		-0.095		0.115
		(0.094)		(0.159)
'New' Fast start$_{-jt}$ [2]		-0.040		-0.075
		(0.026)		(0.052)
p-value [1] = [2]		[0.5731]		[0.2542]

'Recurrent' Fast start$_t$	0.078***		0.164***	
	(0.026)		(0.044)	
'Recurrent' Fast start$_{jt}$ [3]		0.197*		0.090
		(0.102)		(0.148)
'Recurrent' Fast start$_{-jt}$ [4]		0.071***		0.172***
		(0.027)		(0.046)
p-value [3] = [4]		[0.2331]		[0.5968]
Controls	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes
# observations	813,983	813,983	814,585	814,585
# projects	22,995	22,995	23,011	23,011
R^2	0.329	0.329	0.331	0.331

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 (top) and visiting KKBB between May, 23 2010 and December, 31 2015 (bottom). The y-axis is the number of backers (new and recurrent) and the x-axis is the time (monthly).



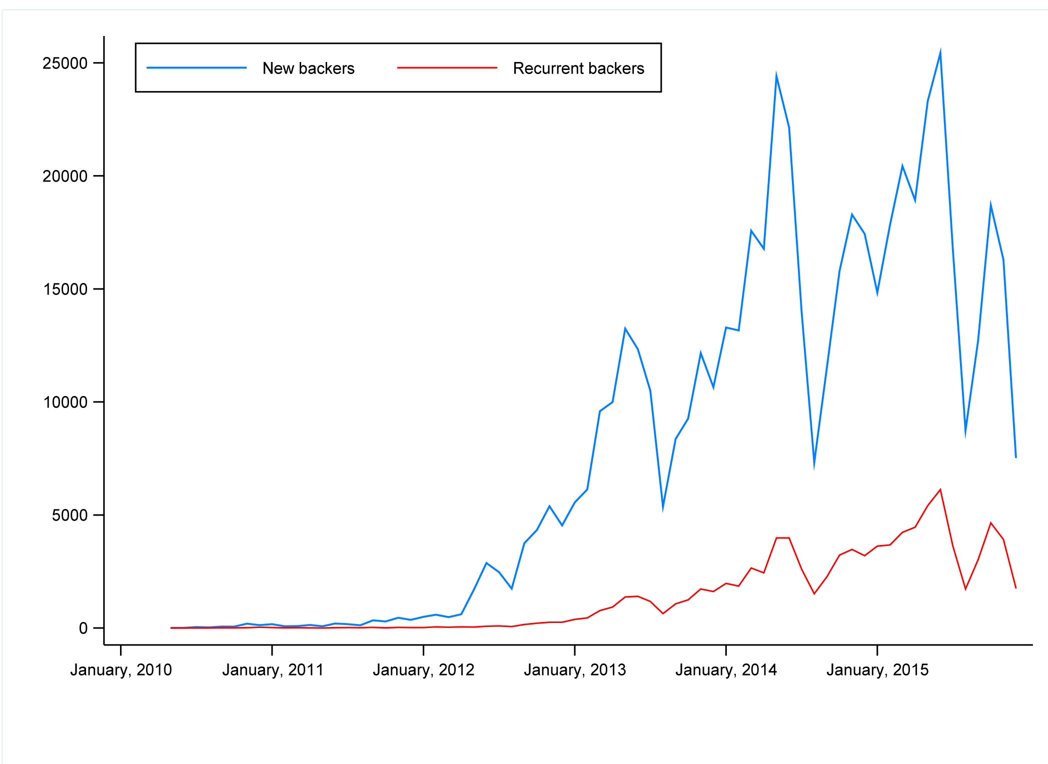


Figure 2. Ulule–KKBB gap over time

The figure presents the evolution of the contribution gap between Ulule and KKBB. The y-axis is the difference in the total number of contributions between Ulule and KKBB and the x-axis is the time (monthly).

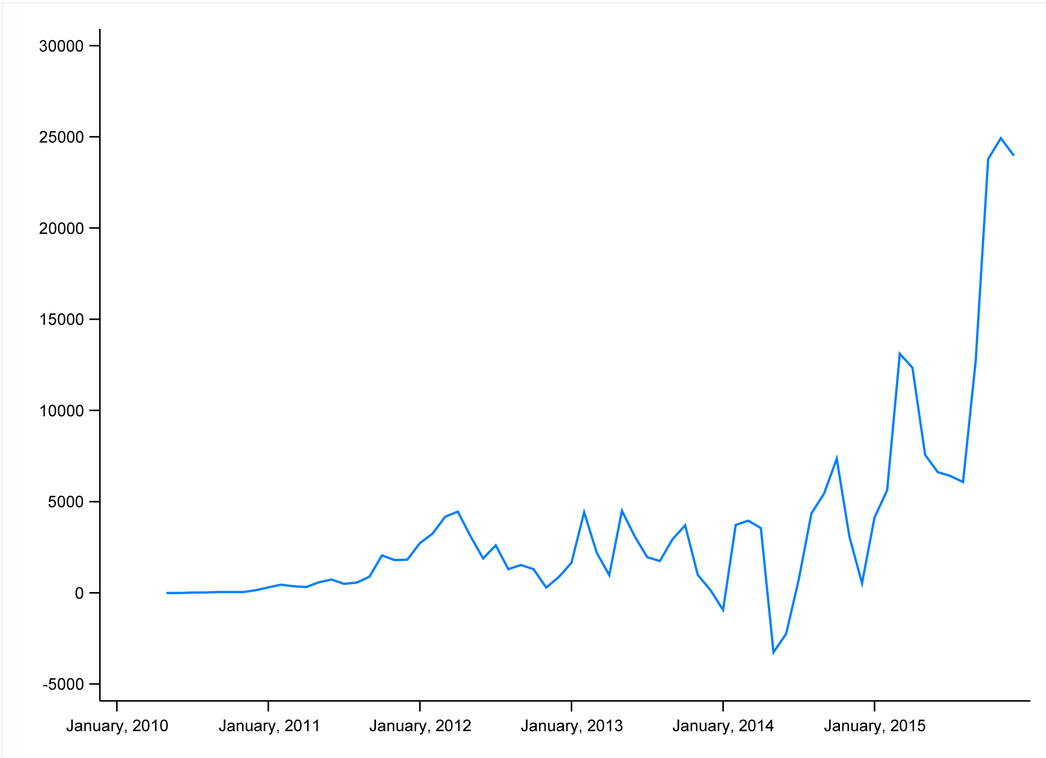


Table 1. Sample summary statistics

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 being featured on the first page of Ulule website during a day and 0 otherwise.

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

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 the platform) 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)		# $contributions_i$ (non-recurrent)		€-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	1.296	0.996	2.300	68.714	266.214
Charities & Citizen (2)	15.71%	1.316	5.734	0.346	2.487	0.970	3.998	65.527	374.061
Childhood & Education (3)	3.39%	1.280	3.454	0.320	1.246	0.960	2.579	57.394	200.271
Comics (4)	5.82%	3.433	27.462	1.658	11.965	1.775	16.156	125.802	926.154
Crafts & Food (5)	4.38%	1.485	3.248	0.393	1.332	1.092	2.379	82.562	242.878
Fashion & Design (6)	3.68%	1.764	5.910	0.474	2.333	1.290	4.380	123.167	588.893
Film & Video (7)	16.40%	1.525	14.130	0.379	3.466	1.147	10.926	75.142	541.091
Games (8)	4.88%	3.472	16.198	1.944	12.305	1.528	6.109	211.210	1,480.725
Heritage (9)	1.39%	1.560	3.161	0.530	1.516	1.030	2.224	122.166	463.942
Music (10)	14.43%	1.563	9.748	0.399	3.420	1.164	6.660	67.257	427.202
Other (11)	3.68%	1.450	6.060	0.405	3.051	1.045	3.748	86.411	475.975
Publishing & Journalism (12)	10.26%	2.714	11.961	0.920	5.120	1.794	7.688	123.736	769.693
Sports (13)	3.54%	0.951	2.648	0.163	0.678	0.788	2.319	59.518	293.292
Stage (14)	6.02%	1.227	2.397	0.312	0.908	0.915	1.832	59.081	179.470
Technology (15)	1.81%	1.608	5.666	0.385	1.887	1.223	4.557	109.833	781.547
All categories	100.00%	1.587	9.747	0.464	3.851	1.123	6.664	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. Within- and cross-project funding dynamics

This table presents fixed-effects estimates of the within- and cross-project funding dynamics 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). The lag of the dependent variable captures within-project dynamics. # $contributions_{-i}$ 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 cross-project dynamics 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 cross-project dynamics across categories. Control variables include # $projects_i$, % goal, Popular. # $projects_i$ is the number of projects within category *i* (in log). % goal is the ratio of the amount raised to targeted goal, Popular is a dummy variable equal to 1 if the project is among the 8 projects being featured on the first page of Ulule website during a day and 0 otherwise. Columns 1-4 and 6 include all observations from all projects, while column 5 excludes the observations of projects when their target goal is reached. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
# $contributions_{i,t-1}$	0.217***			0.215***	0.165***	0.215***
	(0.002)			(0.002)	(0.002)	(0.002)
# $contributions_{-i,t-1}$		0.033***		0.016***	0.017***	
		(0.002)		(0.002)	(0.002)	
# $contributions_{-j,t-1}$			0.089***	0.054***	0.055***	
			(0.003)	(0.003)	(0.003)	
# $contributions_{Art\ \&Photo,t-1}$						0.011***
						(0.001)
# $contributions_{Charities\ \&\ Citizen,t-1}$						0.011***
						(0.002)
# $contributions_{Childhood\ \&\ Education,t-1}$						0.002
						(0.001)
# $contributions_{Comics,t-1}$						0.003***
						(0.001)
# $contributions_{Crafts\ \&\ Food,t-1}$						0.007***
						(0.001)
# $contributions_{Fashion\ \&\ Design,t-1}$						0.002*
						(0.001)
# $contributions_{Film\ \&\ Video,t-1}$						0.006***
						(0.002)
# $contributions_{Games,t-1}$						0.001
						(0.001)
# $contributions_{Heritage,t-1}$						0.014***
						(0.002)
# $contributions_{Music,t-1}$						0.002*
						(0.001)
# $contributions_{Other,t-1}$						0.005***
						(0.001)
# $contributions_{Publishing\ \&\ Journalism,t-1}$						0.007***
						(0.001)
# $contributions_{Sports,t-1}$						0.006***
						(0.002)

# contributions$_{Stage,t-1}$						0.015***
						(0.002)
# contributions$_{Technology,t-1}$						0.005***
						(0.001)
# projects$_{i,t}$	0.004	-0.034***	-0.025***	-0.032***	-0.025***	-0.031***
	(0.007)	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)
% goal$_{t-1}$	-0.155***	-0.077***	-0.078***	-0.157***	-0.120***	-0.158***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.008)	(0.006)
Popular$_t$	1.212***	1.329***	1.331***	1.214***	1.125***	1.215***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.012)	(0.010)
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	681,740	814,960
# projects	23,022	23,022	23,022	23,022	22,760	23,022
R^2	0.481	0.455	0.456	0.482	0.460	0.482

Table 5. Cross-project funding dynamics around fast starts

This table presents difference-in-differences estimates of the effect of project's fast starts on the number of contributions received by projects over their funding cycle. The dependent variable is # contributions$_i$. Fast start$_t$ is a dummy variable equal to 1 during a day a project counts more than 200 (or 500) contributions in its first campaign day and 0 otherwise. Similarly, Fast start$_{j(-j)t}$ is a dummy variable equal to 1 during a day a project counts more than 200 (or 500) contributions in its first campaign day within a category *j* (in other categories -*j*) and 0 otherwise. These dummy variables capture the cross-project dynamics of a project's fast start (within and/or across categories). Appendix Table A4 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 (lagged), Popular and are defined as in Table 4. The sample contains all projects (except the fast starters themselves) 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)	(2)	(3)	(4)
Fast start$_t$	0.015***		0.029***	
	(0.005)		(0.008)	
Fast start$_{jt}$ [1]		0.040**		0.048**
		(0.016)		(0.024)
Fast start$_{-jt}$ [2]		0.014***		0.027***
		(0.005)		(0.008)
p-value [1] = [2]		[0.0860]		[0.3962]
Control variables	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes
# observations	813,983	813,983	814,585	814,585
# projects	22,995	22,995	23,011	23,011
R^2	0.443	0.443	0.448	0.448

Table 6. New backers *vs.* recurrent backers

This table presents estimates of the within- and cross-project funding dynamics generated by both new and recurrent backers 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). Panel A mirrors the first four fixed-effects specifications of Table 4 but differentiates new backers from recurrent backers for each independent variable of interest ('recurrent' means backers having previously contributed at least once either in the project, or in any other projects of the same category, or in any other projects of any other categories). Panel B mirrors the difference-in-differences specifications (i.e., around fast starts) of Table 5 but differentiates new backers from recurrent backers. All the variables are defined as in Tables 4 and 5. 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: Within- and cross-projects funding dynamics

	(1)	(2)	(3)	(4)
# new $\text{contributions}_{i,t-1}$ [1]	0.197***			0.195***
	(0.002)			(0.002)
# recurrent $\text{contributions}_{i,t-1}$ [2]	0.156***			0.154***
	(0.002)			(0.002)
# new $\text{contributions}_{-i,t-1}$ [1]		0.028***		0.015***
		(0.002)		(0.002)
# recurrent $\text{contributions}_{-i,t-1}$ [2]		0.008***		0.002*
		(0.002)		(0.001)
# new $\text{contributions}_{-j,t-1}$ [1]			0.074***	0.045***
			(0.004)	(0.003)
# recurrent $\text{contributions}_{-j,t-1}$ [2]			0.019***	0.011***
			(0.003)	(0.003)
p-value [1] = [2]	[0.000]	[0.000]	[0.000]	-
Control variables	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes
# observations	814,960	814,960	814,960	814,960
# projects	23,022	23,022	23,022	23,022
R^2	0.484	0.455	0.456	0.484

Panel B: Cross-project funding dynamics around fast starts

	>200		>500	
	(1)	(2)	(3)	(4)
'New' Fast start_t	-0.007		-0.020	
	(0.007)		(0.014)	
'New' Fast start_{jt} [1]		-0.023		0.033
		(0.027)		(0.046)
'New' Fast start_{-jt} [2]		-0.007		-0.026*
		(0.008)		(0.015)
p-value [1] = [2]		[0.5733]		[0.2230]

'Recurrent' Fast $start_t$	0.026***		0.056***	
	(0.008)		(0.013)	
'Recurrent' Fast $start_{jt}$ [3]		0.074**		0.057
		(0.032)		(0.044)
'Recurrent' Fast $start_{-jt}$ [4]		0.023***		0.057***
		(0.008)		(0.013)
p-value [3] = [4]		[0.1148]		[0.9961]
Control variables	Yes	Yes	Yes	Yes
Project Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Day of week Fixed Effects	Yes	Yes	Yes	Yes
Funding cycle day Fixed Effects	Yes	Yes	Yes	Yes
# observations	813,983	813,983	814,585	814,585
# projects	22,995	22,995	23,011	23,011
R^2	0.443	0.443	0.448	0.448

Table 7. Project success

This table presents OLS estimates of the effects of recursiveness on project success. In columns 1-4 and 6, the dependent variable, $Success_k$, is a dummy variable equal to 1 if backer's contribution *k* goes to a successful project (i.e., a project that ultimately reaches its target goal) and 0 otherwise. In columns 5 and 7, the dependent variable, Success $ratio_k$, is the amount raised by the project for which backer's contribution *k* goes to divided by the project target goal. Recurrent $backer_k$ is a dummy variable equal to 1 if the backer's contribution *k* is recurrent (depending on the subscript, 'recurrent' refers to either project *i*, or any other projects of the same category of project *-i*, or any other projects of any other categories *-j*) and 0 otherwise. Control variables include Age, €-value first contribution, Campaign duration, Campaign size, Entrepreneur experience, and Cash contribution. Age is the backer's age in years (in log), €-value first contribution is the backer's first project €-amount pledged (in log), Campaign duration is the number of days for which a project accepts funding (in log), Campaign size is the value of the target goal (in log), Entrepreneur experience is the number of launched projects by the entrepreneur, Cash contribution is a dummy variable equal to 1 if the backer contributes using cash possible with Ulule, not KKBB) and 0 otherwise. All the models include a constant, whose coefficient is not reported. In columns 1 to 5, the sample contains all contributions made on the Ulule platform between 5 July 2010 and 29 November 2016. In columns 6 and 7, the sample contains all contributions made on the KKBB platform between 23 May 2010 and 31 December 2015. In all columns, the sample excludes the observations of contributions to projects for which their target goal is reached. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by backer. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Success_{ik}$ (Ulule)				Success $ratio_{ik}$ (Ulule)	$Success_{ik}$ (KKBB)	Success $ratio_{ik}$ (KKBB)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Recurrent $contribution_{ik}$	0.026***			0.028***	0.026***	0.076***	0.027
	(0.002)			(0.002)	(0.004)	(0.022)	(0.021)
Recurrent $contribution_{-i,k}$		0.002**		0.003**	0.078***	0.001	0.012***
		(0.001)		(0.001)	(0.003)	(0.002)	(0.003)
Recurrent $contribution_{-j,k}$			0.012***	0.015***	0.082***	0.005***	0.005***
			(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.004***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
€-value first contribution	0.021***	0.022***	0.022***	0.021***	0.061***	0.046***	0.085***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Campaign duration	-0.023***	-0.023***	-0.023***	-0.023***	-0.219***	0.003***	-0.050***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Campaign size	-0.032***	-0.032***	-0.032***	-0.032***	0.037***	-0.049***	-0.043***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Entrepreneur experience	0.000	0.000	0.000	-0.000	0.006***	0.003**	-0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Cash contribution	0.086***	0.086***	0.086***	0.086***	0.108***	-	-
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	-	-
Country of residence Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	983,324	983,324	983,324	983,324	983,324	194,464	194,464
R^2	0.091	0.091	0.091	0.091	0.275	0.087	0.196

Table 8. Funding cycle timing

This table presents OLS estimates of the effects of recursiveness on funding cycle timing. The dependent variable, $Timing_{ik}$, is the day of the funding cycle at which backer's contribution *k* is made to the project *i* divided by the campaign duration in days and thus ranges between 0 and 1. Recurrent $backer_{ik}$ is a dummy variable equal to 1 if the backer's contribution *k* is recurrent (depending on the subscript, 'recurrent' refers to either any other projects of the same category of project *i*, or any other projects of any other categories -*j*) and 0 otherwise. Control variables include Age, €-value first contribution, Campaign duration, Project size, Entrepreneur experience, and Cash contribution. Age is the backer's age in years (in log), €-value first contribution is the backer's first project €-amount pledged (in log), Campaign duration is the number of days for which a project accepts funding (in log), Campaign size is the value of the target goal (in log), Entrepreneur experience is the number of launched projects by the entrepreneur, Cash contribution is a dummy variable equal to 1 if the backer contributes using cash (possible with Ulule, not in KKBB) and 0 otherwise. All the models include a constant, whose coefficient is not reported. In columns 1 to 3, the sample contains all contributions made on the Ulule platform between 5 July 2010 and 29 November 2016. In column 4, the sample contains all contributions made on the KKBB platform between 23 May 2010 and 31 December 2015. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by backer. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Timing_{ik}$ (Ulule)			$Timing_{ik}$ (KKBB)
	(1)	(2)	(3)	(4)
Recurrent $backer_{-ik}$	-0.025***		-0.026***	-0.017***
	(0.002)		(0.002)	(0.002)
Recurrent $backer_{-jk}$		-0.002**	-0.002*	-0.014***
		(0.001)	(0.001)	(0.001)
Age	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
€-value first contribution	0.006***	0.006***	0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Campaign duration	0.006***	0.006***	0.006***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Campaign size	0.011***	0.011***	0.011***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
Entrepreneur experience	0.001***	0.001**	0.001***	0.027***
	(0.000)	(0.000)	(0.000)	(0.002)
Cash contribution	0.022***	0.022***	0.022***	-
	(0.001)	(0.001)	(0.001)	-
Country of residence Fixed Effects	Yes	Yes	Yes	Yes
Category Fixed Effects	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes
# observations	1,300,773	1,300,773	1,300,773	638,673
R^2	0.082	0.082	0.082	0.086

Table 9. Recurrent contributions over time

The table presents the evolution of contributions by category and over time on both platforms. In Panel A, the sample includes the universe of projects on the Ulule platform between July 5, 2010 and November 29, 2016. In Panel B, the sample includes the universe of projects on the KKBB platform between May 23, 2010 and December 31, 2015. The category classification is as reported by Ulule and KKBB, respectively. The statistics presented are the average number of recurrent contributions per project/day by category and year. CAGR is the compound annual growth rate.

Panel A: Ulule platform

	2010	2011	2012	2013	2014	2015	2016	All years	CAGR
Art & Photo	0.063	0.070	0.147	0.181	0.309	0.493	0.558	0.386	0.365
Charities & Citizen	0.089	0.074	0.115	0.183	0.229	0.455	0.445	0.346	0.258
Childhood & Education	.	0.157	0.124	0.145	0.220	0.347	0.376	0.320	0.157
Comics	0.075	0.051	0.220	0.555	1.002	1.961	2.464	1.658	0.647
Crafts & Food	0.083	0.116	0.187	0.237	0.246	0.474	0.524	0.393	0.302
Fashion & Design	0.103	0.113	0.184	0.242	0.300	0.509	0.744	0.474	0.326
Film & Video	0.086	0.070	0.156	0.335	0.304	0.592	0.571	0.379	0.311
Games	0.153	0.271	0.654	0.886	0.950	2.862	3.598	1.944	0.571
Heritage	.	.	0.436	1.318	0.412	0.507	0.607	0.530	0.068
Music	0.118	0.097	0.148	0.231	0.294	0.424	0.674	0.399	0.283
Other	0.333	0.089	0.057	0.198	0.246	0.356	0.530	0.405	0.068
Publishing & Journalism	0.094	0.158	0.271	0.570	0.823	1.241	1.041	0.920	0.410
Sports	0.085	0.066	0.106	0.108	0.119	0.199	0.251	0.163	0.166
Stage	0.072	0.071	0.140	0.196	0.273	0.345	0.467	0.312	0.306
Technology	0.108	0.144	0.190	0.405	0.479	0.412	0.385	0.385	0.199
All categories	0.091	0.090	0.176	0.289	0.321	0.578	0.675	**0.464**	**0.331**

Panel B: KKBB platform

	2010	2011	2012	2013	2014	2015	All years	CAGR
Adventure & Sport	0.067	0.024	0.024	0.035	0.033	0.027	0.031	-0.141
Arts	0.023	0.034	0.075	0.074	0.079	0.070	0.074	0.203
Comics	.	.	.	0.106	0.062	0.080	0.073	-0.091
Ecology	.	.	0.048	0.064	0.097	0.088	0.087	0.167
Education	.	0.040	0.066	0.060	0.048	0.047	0.051	0.034
Fashion & Design	.	0.063	0.062	0.066	0.054	0.049	0.055	-0.047
Film & Video	0.103	0.064	0.069	0.082	0.080	0.072	0.077	-0.057
Games	0.000	0.091	0.015	0.031	0.059	0.050	0.047	-0.114
Gastronomy	.	.	0.189	0.076	0.073	0.063	0.071	-0.241
Heritage	.	.	.	0.000	0.050	0.054	0.052	0.032
Journalism & Publishing	.	0.040	0.080	0.090	0.087	0.082	0.085	0.157
Music	0.046	0.046	0.072	0.073	0.076	0.076	0.075	0.085
Others	.	0.050	0.083	0.060	0.074	0.066	0.068	0.056
Performing Arts	0.104	0.050	0.067	0.073	0.080	0.079	0.077	-0.045
Solidarity	0.020	0.052	0.055	0.062	0.050	0.045	0.050	0.146
Web & Tech	0.000	0.042	0.068	0.070	0.052	0.044	0.054	0.006
All categories	0.054	0.047	0.071	0.072	0.071	0.065	**0.069**	**0.030**