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Spillovers in Crowdfunding

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ABSTRACT

We use novel entrepreneur-backer data to study the extent to which spillovers arise between projects displayed on crowdfunding platforms. 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 spillovers" account for 4% in the increase of contributions that projects generate on a daily basis. We show that recurrent backers are an important transmission channel of cross-project spillovers: 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. These findings have significant implications for digital platform management and competition dynamics.

JEL Classification: D43, G23, L14, L26, L86

1 | Introduction

1.1 | Motivation

Crowdfunding platforms (CFPs) serve as key intermediaries between entrepreneurs and backers, generating a complex array of external effects among them. Backers can influence one another when interacting with a CFP. As contributions occur in sequence, subsequent backers may rely on past contributions to infer a project's quality and likelihood of success. This raises the question of *within-project dynamics*: To what extent do the contributions of early backers affect the decisions of later backers? Entrepreneurs also affect each other when joining a CFP. On the one hand, they compete for backers' support, which can negatively impact their chances: the more projects displayed on the CFP, the lower the likelihood of any individual project being funded. On the other hand, entrepreneurs benefit from each other's presence because they collectively boost the overall engagement of backers. Backers are more inclined to join a CFP with a diverse and large group of entrepreneurs. These conflicting forces raise the question of *cross-project spillovers*: Do simultaneous projects diminish or enhance each other's funding?

To date, the crowdfunding literature has extensively explored the dynamics of funding within individual projects, largely overlooking the phenomenon of spillovers between different projects. This emphasis on within-project dynamics is understandable, as the unique interaction among backers distinguishes crowdfunding from traditional funding models. However, this focus becomes paradoxical when we consider the essential role that CFPs play in connecting backers with entrepreneurs. Without these platforms offering a variety of projects for backers to consider, no single project would secure funding. Therefore, it is crucial to evaluate cross-project spillovers in conjunction with within-project dynamics. This paper aims to address that gap.

1.2 | Background and Data

Our analysis focuses on the French reward-based crowdfunding market.[1] This market, the largest in Europe, is characterized by the presence of two dominant CFPs: Ulule and KissKissBankBank (thereafter KKBB); the other French reward-based CFPs are comparatively very small and only active in niche market segments. This duopolistic market structure is similar to that observed in the United States, where Kickstarter and Indiegogo largely dominate. Thanks to the unique and rich data that we obtained from both Ulule and KKBB, we can study the sequences of backers' funding decisions *within* a particular project and *across* different projects. Critically, backers on these platforms can observe the other backers on a specific project and their respective contributions, unlike on Kickstarter and Indiegogo where backers can only observe aggregated information about other backers and contributions to a particular project. Our primary analysis using Ulule data covers more than 1.3 million backers' funding decisions on about 24,000 entrepreneurial projects between 2010 and 2016. We corroborate our analysis with a similar set of data from KKBB over 2010 and 2015.

1.3 | Strategy

Our analysis proceeds in three steps. First, we compare the decisions of *recurrent backers*—those who contribute repeatedly—and *new backers*—those who contribute only once. We observe on Ulule and KKBB that recurrent backers differ significantly from new backers. Compared to new backers, they are more likely to contribute to successful projects and tend to do so earlier in the campaign. Combined, these observations suggest that recurrent backers are less influenced by other backers and wield more influence over other backers, which supports the idea that recurrent backers initiate social learning.[2] Consequently, by providing informational value to other backers, recurrent backers may act as conduits for positive cross-project spillovers. However, two additional forces influence the relationship between contributions to different projects. On the one hand, increased contributions to one project tend to result in reduced contributions to others as entrepreneurs compete for limited funds. On the other hand, as the platform becomes more appealing, it attracts a greater number of contributions, potentially benefiting all projects. This may result in a spurious correlation between past contributions to a specific project and current contributions to others.

Against this backdrop, the second step of our analysis aims to understand the interaction between these forces. We build a simple theoretical framework. We consider a CFP that proposes a given set of projects to two types of backers on two consecutive days. Following the empirical observations made in the first step, we assume that recurrent backers decide before new backers and in a more independent and informed way. By aggregating the decisions of the two types of backers, we can identify the various channels through which past contributions to one project affect current contributions to another. We can also appreciate the respective influence of the different parameters of the model, namely the number of projects, their degree of differentiation, the share of recurrent backers, the degree of herding among backers, and the platform's rate of growth. This allows us to formulate predictions regarding within-project dynamics, cross-project spillovers, and their determinants.

In the third step, we test these predictions by estimating a dynamic panel model using the standard fixed-effects estimator as well as a difference-in-differences estimator.

1.4 | Results

Our empirical results show that the influence of recurrent backers extends beyond the funding campaign of a single project; it also impacts other projects recurrent backers choose to support over time. As a result, recurrent backers' decisions forge a positive connection between current contributions to one project and future contributions to others. In essence, recurrent backers help transfer positive funding momentum from one project to another. Our central fixed-effects estimates establish the existence of such positive *cross-project spillovers*: The number of contributions generated by a project daily is about 1% (4%) higher following a doubling in the number of contributions within (across) categories. The number of contributions generated by a project daily is also approximately 16% higher following a doubling in the number of contributions within the same project.[3] This second result confirms the existence of positive *within-project dynamics*, which have already been documented in the literature (e.g., Agrawal, Catalini, and Goldfarb 2015; Kuppuswamy and Bayus 2017). Both results hold regardless of the number of projects simultaneously displayed on the CFP.

These results on within-project dynamics and cross-project spillovers highlight the pivotal role of recurrent backers. When we differentiate between the contributions of recurrent and new backers in our central analysis, we demonstrate that each group exerts distinct effects on within-project dynamics and cross-project spillovers. To more precisely assess the causal impact of positive cross-project spillovers, we concentrate on *fast starters*—projects that garner an unexpectedly high number of pledges on their first day. By employing a difference-in-differences research design, we explore the spillover effects following the initial day of these fast starters. Our difference-in-differences estimates indicate that cross-project spillovers lead to approximately a 4% increase in the daily contributions received by a project within the same category. Importantly, we also find that fast starters produce significantly larger cross-project spillovers when they have a relatively larger proportion of contributions from recurrent backers than new backers. Our local projections further show that cross-project spillovers persist over 3–4 days and then vanish.

1.5 | Implications

Our findings have significant implications for the management and competitive strategy of CFPs. From a managerial standpoint, a key takeaway for CFP managers is the distinct behavior of recurrent backers, who are recognized as *social influencers*. Our research shows that projects with a higher proportion of recurrent backers tend to generate more contributions, suggesting that retaining existing backers yields higher returns than solely focusing on acquiring new ones. Our analysis also indicates that the success of a CFP hinges on the mix of projects launched simultaneously on the platform. Given the complementarities between projects, as shown by the presence of positive cross-project spillovers, CFPs can boost total contributions by selecting an optimal project mix. Our study also underscores the importance of providing information on the funding decisions of recurrent sponsors. Platforms like Ulule and KKBB leverage this by publicly sharing such information, setting themselves apart from other major CFPs like Kickstarter and Indiegogo.

From a competitive standpoint, our findings provide further evidence that reward-based crowdfunding markets are inherently inclined toward dominance by a single platform or a limited few. The documented spillover effects amplify the positive feedback loops created by cross-side network effects between entrepreneurs and backers (Belleflamme, Omrani, and Peitz 2015). Consequently, a CFP that outpaces its competitors in growth may secure a self-sustaining competitive edge, ultimately leading to market dominance. Our analysis suggests that a critical factor influencing the growth trajectory of CFPs is the retention rate of recurrent backers. This is illustrated by the widening gap in size and growth between Ulule and KKBB during our study period. For smaller CFPs, survival prospects lie in specialization (identifying the right niche) or consolidation (merging with other CFPs). Beyond the French context, Ziegler, Shneor, and Wenzlaff (2021) report an increase in market concentration in crowdfunding worldwide. These competition implications align closely with the ongoing policy debate on the dominance of BigTech platforms (Crémer et al. 2023).

1.6 | Related Literature

The body of research on crowdfunding has expanded significantly in recent years (for a survey, see Lambert 2024). Within this literature, our study engages with campaign dynamics and crowd heterogeneity in the context of reward-based crowdfunding.

1.6.1 | Campaign Dynamics

Mollick (2014) provides early insights into the dynamics driving campaign success in a large cross-sectional sample of Kickstarter projects, showing that quality signals matter. Kuppuswamy and Bayus (2017) rather concentrate on the dynamics of project contributions over time (i.e., within-project dynamics in our parlance). They find that backers on Kickstarter are more likely to pledge money on projects approaching their target goal. Several other papers have shown evidence of backers inferring information from the decisions of others—a form of social learning, as discussed by Mobius and Rosenblat (2014). Zhang and Liu (2012) uncover that lenders infer the creditworthiness of borrowers by observing lending made by others on a leading marketplace lending platform (Prosper in the United States). Zhang and Liu (2012) led to empirical papers correlating cumulative prior contributions with future contributions in various crowdfunding models, generally finding positive correlations (e.g., Agrawal, Catalini, and Goldfarb 2015; Smith, Windmeijer, and Wright 2015; Hornuf and Schwienbacher 2018; Kim et al. 2020). Astebro et al. (2024) focus, like we do, on the most recent contributions. They find that the likelihood of a contribution on an equity-based crowdfunding campaign is robustly affected by the size of the most recent contribution, rationalizing the idea that larger contributions are seen as quality signals by the crowd while smaller contributions are not seen as such. Their findings align with Van de Rijt et al. (2014) and Zaggl and Block (2019), who present evidence from randomized field experiments on Kickstarter that small contributions reduce follow-up contributions. We add to these papers by confirming the existence of within-project dynamics and highlighting the specific influence of recurrent backers, whose role underscores the importance of public information in reward-based crowdfunding. Indeed, unlike on Kickstarter (on which most papers are based), on Ulule the current and past funding decisions of individual backers are observable to other backers.[4] This distinguishing feature of our data allows us to study the transmission channel behind campaign dynamics.

Crowdfunding dynamics are also studied theoretically, using the angle of contribution games in which positive externalities can lead to free-riding and miscoordination. Among the recent contributions, Ellman and Fabi (2022) characterize in a dynamic model how transparency and design policies can impact funding outcomes, providing insights into the mechanisms that drive campaign success and overall welfare in CFPs. Deb, Oery, and Williams (2024) show that donor contributions act as costly signals to encourage socially productive investments in the face of coordination challenges; they also demonstrate how a strategic leadership donor can promote coordination by dynamically signaling their valuation, thereby increasing the likelihood of campaign success. Cong and Xiao (2024) develop a model in which backers' payoff interdependence results in information cascades. Astebro et al. (2024) also study herding theoretically. They show that large investments provide positive signals about project quality, while periods without investment convey negative information. Information cascades are found to occur only when insufficient positive signals are generated. The study demonstrates that less-informed investors are more susceptible to herding effects, particularly in the early stages of a campaign. Although our theoretical framework is less sophisticated, it departs from these papers by analyzing cross-project spillovers and disentangling the factors that may influence them.

Interestingly, all these papers focus on the evolution of successive contributions to a given project (within-project dynamics) but remain silent about the potential link between current contributions to one project and past contributions to *other* projects (cross-project spillovers). To our knowledge, the only exception is Soublière and Gehman (2020), who rely on a sample of Kickstarter projects to show cross-sectional evidence suggesting that the successes and failures of some projects affect the amount raised by other projects.[5] The granularity of our entrepreneur-backer data and the dynamic setting we exploit allows us to capture the effect of cross-project spillovers—after controlling for within-project dynamics, project and time fixed effects—and document the heterogeneous learning role of backers.

In sum, our contribution lies in demonstrating that spillovers between projects, both within and across categories, are critical to fully apprehending crowdfunding dynamics and the role of platforms. Importantly, our unique data on the two largest reward-based CFPs in France allow us to derive implications for platform growth and competition.

1.6.2 | Crowd Heterogeneity

The majority of papers examining the link between crowdfunding dynamics and crowd heterogeneity focuses on equity- and loan-based crowdfunding, or marketplace lending, and stresses the influence of "sophisticated" or "experienced" investors (e.g., Hornuf and Schwienbacher 2018; Kim and Viswanathan 2018; Vismara 2018; Gal-Or, Gal-Or, and Penmetsa 2019; Vallee and Zeng 2019). Because "experts" or "professionals" backers are absent and/or cannot be identified, the roles of different types of backers has been much less studied in the context of reward-based crowdfunding.[6] An exception is Rodrìguez-Garnica, Gutiérrez-Urtàga, and Tribo (2024), who suggest that backers self-select into early or late backers based on their information processing abilities. In particular, early backers tend to be better-informed and make decisions based on available information and signals from the creator, while late backers are typically less informed and rely more on herding behavior, following the decisions of early backers. The authors show that this self-selection process leads to an information cascade that improves the quality of funding decisions, even without identifiable expert backers. However, it is unclear how later backers can identify that early backers are better-informed (and how early backers were able to acquire this better information in the first place). Arguably, it is only when a platform makes visible the current and past funding decisions of individual backers that inference can be made about who the "expert" or "sophisticated" backers are. As already explained, this is what Ulule and KKBB do (in contrast with Kickstarter). In this respect, the study by Petit and Wirtz (2022) shares some similarities with ours. Considering only cultural projects on Ulule, they show that experienced backers contributing early correlate with campaign success, suggesting a certification role of these backers. They do not consider, among other things, the role these recurrent backers can have in generating cross-project spillovers.

1.7 | Structure

The rest of the paper runs as follows. In Section 2, we introduce Ulule and KKBB and describe our data and key variables. In Section 3, we identify the specific characteristics of recurrent backers. In Section 4, we develop our theoretical framework and formulate a set of testable predictions. In Section 5, we present the results of our empirical estimations on within-project dynamics and cross-project spillovers, highlighting the role of recurrent backers. In Section 6, we discuss the implications of our results for CFP growth and competition. In Section 7, we conclude.

2 | Background, Data, and Variables

Ulule and KKBB are the two largest European reward-based CFPs. The French reward-based crowdfunding market is akin to a duopoly: Ulule and KKBB are the two main players of the market, while a handful of very small reward-based CFPs also operate either in niche segments, such as Miimosa in agriculture, or in specific regions, such as Kengo in Brittany.[7] This duopoly bears similarities to the reward-based crowdfunding market in the United States, which is dominated by Kickstarter and Indiegogo. In 2016 (the last year of our sample), France raised more than €50 million through reward-based crowdfunding (Ziegler and Shneor 2020, p.58). We perform our analysis using both Ulule and KKBB data. However, we describe below Ulule in greater detail as this CFP is the main focus of our analysis.

Opened to the public in July 2010, Ulule (www.ulule.com) has rapidly grown as the largest CFP in France. By October 2024, Ulule attracted close to 6 million registered members and successfully financed over 48,000 projects. Since its inception, Ulule has become an important source of capital for early-stage projects, especially in the arts and creativity-based industries (e.g., recorded music, film, video games). For comparison, Kickstarter (www.kicksarter.com)—the world's dominant reward-based CFP today—was launched in 2009 and has since enabled the successful financing of over 267,000 creative projects, with nearly 24 million backers contributing. This comparison suggests that Ulule's activities are non-negligeable.

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 presale to start production) or a financial objective (the entrepreneur sets ex ante the minimum capital requirement to bring their entrepreneurial project to life). In the parlance of crowdfunding, Ulule uses an All-or-Nothing (AoN) reward-based scheme in which entrepreneurs receive the proceeds of their campaign only if the objective is reached (they receive nothing otherwise).[8] Ulule relies on a standard fee structure by charging a commission rate (starting at 6.67% on the first tranche and decreasing to 4.17% on the last tranche), which only applies to the amounts collected by successful projects.

Figure 1 provides screenshots of ongoing projects displayed on Ulule. As it can be seen in Panel A, Ulule has a design similar to most reward-based CFPs. Each project page includes a description of the project (a video is usually provided), the financing progress, a menu of rewards, a chat box, and a comment page. Panel A exhibits the page of a project with a financial objective (screenshot at the top) and a presale objective (screenshot at the bottom). As shown in Panel B, Ulule also discloses the list of backers, with the most recent backer showing up first. By visiting the project page, prospective backers can observe who previously contributed to the project, for which €-amount and for which reward. Furthermore, prospective backers are able to identify recurrent backers. If a user clicks on another backer's pseudonym, they can see the other projects (if any) the backer previously contributed to and whether these other projects are still ongoing (Panel C). This is an important feature of the CFP for spillovers between projects to materialize. We note that most reward-based CFPs, such as Kickstarter, do not make visible detailed information about a project's backers to prospective backers. These reward-based

(a) Example of a project main page

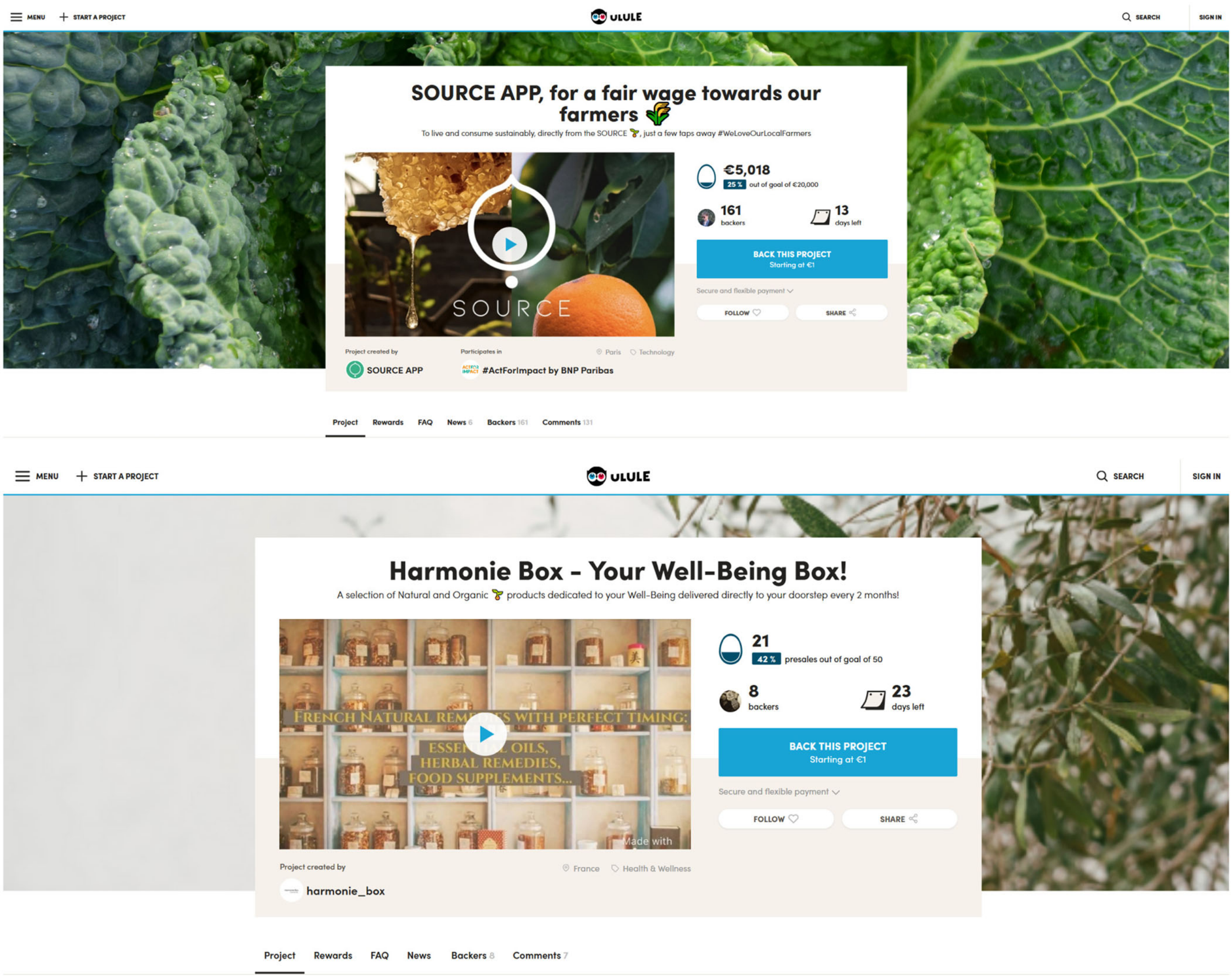


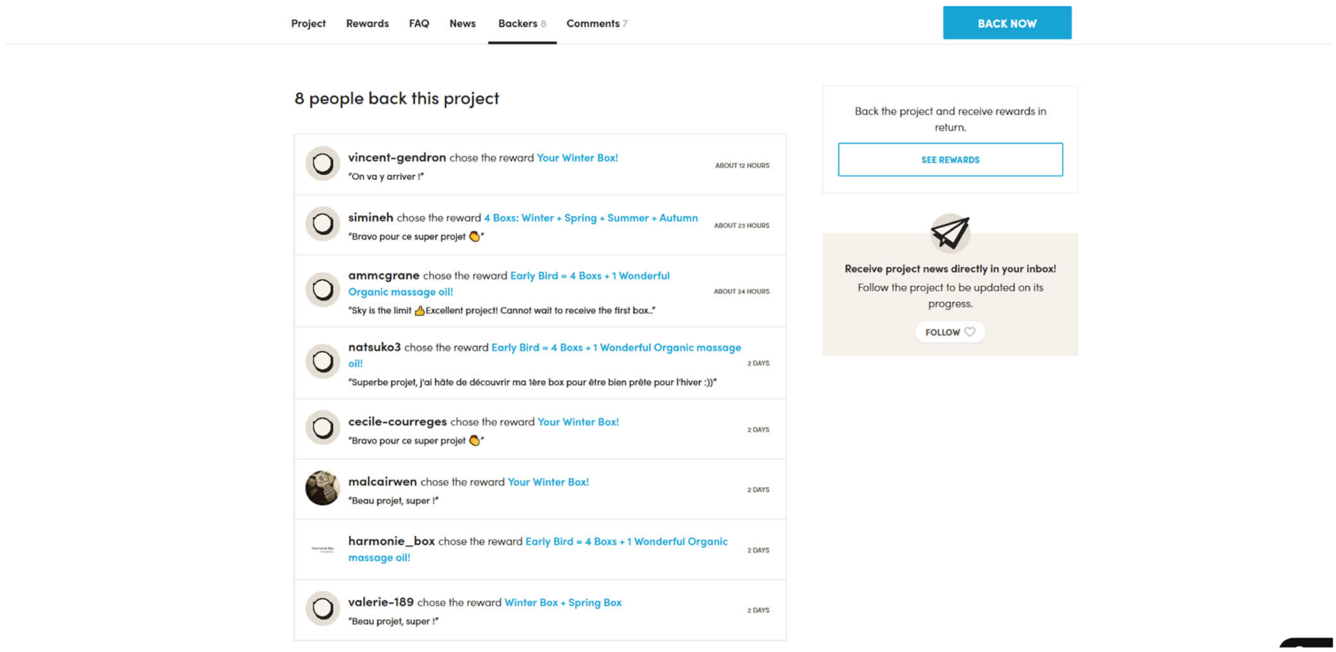
FIGURE 1 | Screenshots of Ulule project pages. *Note:* The figure presents screenshots of Ulule project pages. Panel a shows the main page of an ongoing project with a financial objective (top) and a project with a presale objective (bottom), Panel b shows the tab "Backers" of the project with a presale objective shown in Panel a (bottom), and Panel c shows one of the recurrent backers' page (i.e., the page showing up when a prospective backer clicks on the recurrent backer page). [Color figure can be viewed at wileyonlinelibrary.com]

CFPs typically only report the number of backers to a project without providing the option to view the list of backers (Kim, Newberry, and Qiu 2022).

Our data set 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 the universe of 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 almost 24,000 projects, out of which three third were successfully funded.

Table 1 presents statistics on all contributions made by recurrent backers (see Panel A). We note that 27.6% of the over 1.3 million backers are recurrent in our sample.[9] During our sample period, recurrent backers in the 25th percentile contributed to two projects on average, while those in the 75th percentile backed 7 projects on average. The maximum number of contributions by a recurrent backers is 579.[10] Table 1 shows similar statistics on contributions by recurrent backers broken down by category and projects: 16.4% of total contributions are made by backers recurrent in the same category (median number of contributions is 2), while only 6.3% contributions are made by backers who already contributed to the same project before (median is also 2). Table 1 also reports in Panel B the fraction of invalid contributions, which are ones initially counted in the campaign but later withdrawn by the backer, most often due to insufficient funds in their account. They represent less than 0.2% of contributions in our sample (a total of 2267 invalid contributions), and recurrent backers do not make comparatively more invalid contributions than new backers. The key insight from Table 1 is the important fraction of recurrent backers. This importance is likely acknowledged by Ulule, as it dedicates a Top 5 list of backers ("Ululers") based on recurrence.

(b) Example of tab "Backers"



(c) Example of a recurrent backer's page

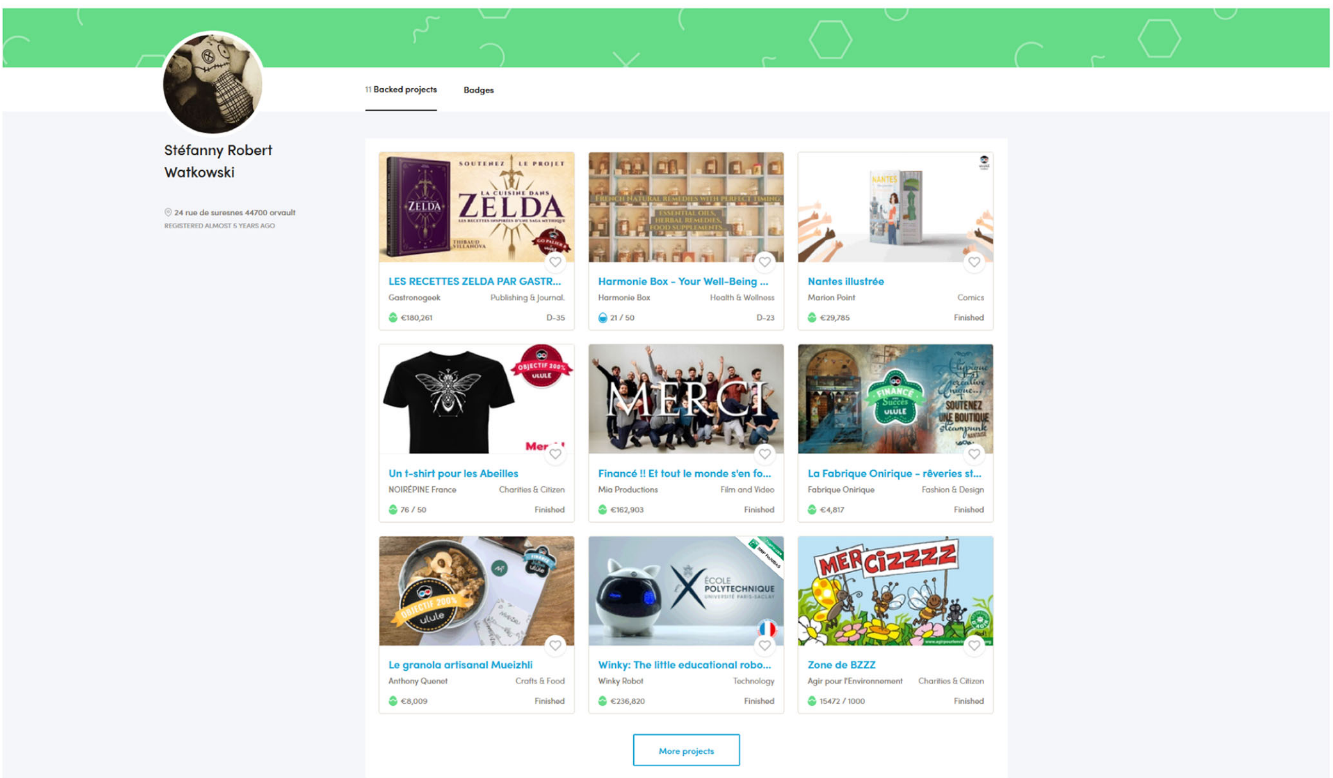


FIGURE 1 | (Continued)

Next, Table 2 presents statistics on 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

TABLE 1 | Contributions by recurrent backers.

Panel A: All contributions							
Variable	**Mean**	**25pc**	**Median**	**75pc**	**Min**	**Max**	**Obs**
Recurrent contributions (dummy)	0.276	0	0	1	0	1	1,331,452
Recurrent category contributions (dummy)	0.164	0	0	0	0	1	1,331,452
Recurrent project contributions (dummy)	0.063	0	0	0	0	1	1,331,452
Contributions by recurrent backers	10.392	2	4	7	2	579	368,182
Category contributions by recurrent backers	8.690	2	3	6	2	538	219,329
Project contributions by recurrent backers	4.901	2	2	4	2	117	84,822

Panel B: Invalid contributions							
Variable	**Mean**	**25pc**	**Median**	**75pc**	**Min**	**Max**	**Obs**
Invalid contributions (dummy)	0.002	0	0	0	0	1	1,331,452
Invalid recurrent contributions (dummy)	0.002	0	0	0	0	1	368,182
Invalid recurrent category contributions (dummy)	0.002	0	0	0	0	1	219,329
Invalid recurrent project contributions (dummy)	0.003	0	0	0	0	1	84,822
Invalid contributions by recurrent backers	2.303	1	1	2	1	12	676
Invalid category contributions by recurrent backers	2.661	1	2	3	1	12	478
Invalid project contributions by recurrent backers	3.743	2	2	4	1	12	257

Note: The table presents summary statistics on (valid and invalid) contributions by recurrent backers. A recurrent contribution is one that is made by a backer who has contributed to a project at least once before. The contributions made by Ulule's partners that back projects on a recurrent basis are also counted as recurrent contributions; there are 10 partners (with user ID 548662, 268813, 7313, 107894, 129921, 6030, 354924, 328141, 84313, 548669) during our sample period that contributed between 1 and 579 projects. Panel A focuses on all contributions, while Panel B on invalid contributions only. An invalid contribution refers to one that was initially counted in the campaign but later withdrawn by the backer, most often due to insufficient funds in their account. *Recurrent contributions (dummy)* is a dummy variable equal to 1 if the contribution received by a project is made by a recurrent backer and 0 otherwise. *Recurrent category contributions (dummy)* is a dummy variable equal to 1 if the contribution received by a project is made by a backer recurrent in the category of the project and 0 otherwise. *Recurrent project contributions (dummy)* is a dummy variable equal to 1 if the contribution received by a project is made by a backer recurrent in within the same project and 0 otherwise. *Contributions by recurrent backers* are the number of contributions made by recurrent backers. *Category contributions by recurrent backers* are the number of contributions made by backers recurrent in one category. *Project contributions by recurrent backers* is the number of contributions made by backers recurrent within the same project. *Invalid contributions (dummy)* are a dummy variable equal to 1 if the contribution received by a project is invalid and 0 otherwise. The other variables preceded by "invalid" are defined similarly to their counterparts, except they count only invalid contributions. The sample includes the universe of projects on the Ulule platform between July 5, 2010 and November 29, 2016.

incentivizing backers to come back on the platform, particularly the categories *Comics* and *Games*. In Supporting Information S1: Table OA1, we also document the extent to which the successive contributions of recurrent backers go to projects within the same category or across different categories. We observe that some categories are more independent than others. This is the case of the category *Games*, of which 59.2% of contributions are made by recurrent backers and relatively few of them (32.4%) contribute in other categories. In contrast, only a small fraction of contributions in categories like *Music* comes from recurrent backers (26.5%), while a large fraction of these recurrent backers contribute to other categories (64.0%). In general, the values along the diagonal of Supporting Information S1: Table OA1 indicate that those who backed a project within a given category are more likely to contribute to another project in the same category than in another category, potentially reflecting their preferences. Furthermore, a meaningful number of backers tend to pledge money repeatedly on the same project according to values in bold in Supporting Information S1: Table OA1 (see also Table 1).

Table 3 turns to the empirical analysis of within-project dynamics and cross-project spillovers, and presents summary statistics for the key variables. The first set of variables measures funding dynamics. 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).[11] 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

TABLE 2 | Contributions by category.

Category	% Total platform contributions	*Contributions$_i$* (all) Mean	*Contributions$_i$* (all) Std dev	*Contributions$_i$* (recurrent) Mean	*Contributions$_i$* (recurrent) Std dev	*Contributions$_i$* (non-recurrent) Mean	*Contributions$_i$* (non-recurrent) Std dev	*Volume$_i$* Mean	*Volume$_i$* 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

Note: 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. *Volume$_i$* is the total value (in €) of contributions received by project i during a day.

TABLE 3 | Sample summary statistics.

Variable	Mean	Std dev	Median	Min	Max	Obs
$Contributions_i$	1.587	9.747	1.000	0.000	4105.000	838,931
$Contributions_{-i}$	96.727	104.011	71.000	0.000	4178.000	838,931
$Contributions_{-j}$	837.055	551.612	761.000	0.000	5452.000	838,931
$Volume_i$	79.899	511.822	5.000	0.000	109,874.000	838,931
$Volume_{-i}$	4790.567	5277.181	3435.276	0.000	121,840.500	838,931
$Volume_{-j}$	42,653.110	28,938.600	37,688.400	0.000	221,388.600	838,931
Competing projects$_i$	63.159	46.243	53.000	1.000	219.000	838,931
Financing progress	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

Note: 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. $Volume_i$ is the total value (in €) of contributions received by project i during a day. $Volume_{-i}$ 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. $Volume_{-j}$ 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. *Competing projects*$_i$ is the number of projects within category i. *Financing progres*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 eight projects being featured on the first page of Ulule website during a day and 0 otherwise.

deviation is 104 (552). Again, similar insights apply for the volume of the other category/platform-wide contributions.

The second set of variables includes time-varying project-level characteristics that have been shown in the literature 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 that are, 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).

We also test the robustness of our results using data on the universe of projects listed on KKBB (www.kisskissbankbank.com). KKBB also uses an AoN scheme. Since KKBB inception in September 2009, about 3.1 million backers contributed to approximately 30,000 successfully funded projects. With a similar platform design and geographical scope, KKBB is the main competitor of Ulule. The KKBB sample covers the pledge decisions of almost 650,000 backers on 14,000 projects over the period between May, 23 2010 and December 31, 2015. We further present our KKBB sample and statistics when conducting the robustness tests.

3 | Recurrent Backers

By contributing to different projects over time, recurrent backers accumulate experience, making them behave differently than new (one-time) backers. We explore this idea by testing whether recurrent backers tend to contribute (1) more to projects that end up being successful and (2) earlier in a campaign than new backers.

To examine these associations, we aggregate our data set at the individual contribution level and perform linear regressions of the following specification:

$$y_{ik} = \alpha + \beta_1 X_{ik} + \beta_2 X_{-ik} + \beta_3 X_{-jk} + \boldsymbol{\gamma} \boldsymbol{X}_{ijk} + \varepsilon_{ik}. \qquad (1)$$

The dependent variable, y_{ik}, stands for either Success_{ik} or Timing_{ik}: Success_{ik} takes the value of one if a backer's contribution k is made on a project i that will eventually end up being successful (0 otherwise), and Timing_{ik} is the day of the campaign when a backer's contribution k is made to project i divided by the campaign duration in days. Next, α is a constant term, X_{ik} takes the value of 1 if the contribution k is made by a backer recurrent within project i (0 otherwise), X_{-ik} takes the value of 1 if the contribution k is made by a backer recurrent within the same category of project i (0 otherwise), and X_{-jk} takes the value of 1 if the contribution k is made by a backer recurrent in any other categories j except the category of project i (0 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.

Tables 4 and 5 report our estimates of Equation 1.[12] The results across columns 1–5 of Table 4 show support for our prediction about recurrent backer i's ability to spot successful projects. 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, suggesting 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

TABLE 4 | Project success.

	$Success_{ik}$				$Success\ ratio_{ik}$
	(1)	(2)	(3)	(4)	(5)
$Recurrent\ backer_{ik}$	0.026***			0.028***	0.026***
	(0.002)			(0.002)	(0.004)
$Recurrent\ backer_{-i,k}$		0.002**		0.003**	0.078***
		(0.001)		(0.001)	(0.003)
$Recurrent\ backer_{-j,k}$			0.012***	0.015***	0.082***
			(0.001)	(0.001)	(0.002)
Age	−0.001***	−0.001***	−0.001***	−0.001***	−0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
First contribution value	0.021***	0.022***	0.022***	0.021***	0.061***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Campaign duration	−0.023***	−0.023***	−0.023***	−0.023***	−0.219***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Campaign size	−0.032***	−0.032***	−0.032***	−0.032***	0.037***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Entrepreneur experience	0.000	0.000	0.000	−0.000	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
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
Category fixed effects	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	983,324	983,324	983,324	983,324	983,324
R^2	0.091	0.091	0.091	0.091	0.275

Note: The table presents OLS estimates of the effects of recursiveness on project success. In columns 1–4, 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 column 5, 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. First contribution value, Campaign duration, Campaign size, Entrepreneur experience, and Cash contribution*. *Age* is the backer's age in years (in log), *First contribution value* 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) and 0 otherwise. All the models include a constant, whose coefficient is not reported. The sample contains all contributions made on the Ulule platform between July 5, 2010 and November 29, 2016. 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.

contributed to the project, while this increased probability is 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 examine 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 another category) than project i. Although these results suggest that recurrent backers are more likely to contribute to projects that ultimately succeed, a word of caution is warranted. This regression framework does not allow us to discern whether their success is due to better project selection or improved project outcomes.

The results from Table 5 also support our prediction about recurrent backer i's likelihood to pledge money earlier. In columns 1–3, we estimate the effect of recurrent backers within category $-i$ and across categories $-j$ on funding cycle timing. The specifications are the same as before, except that we do not estimate 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,

TABLE 5 | Funding cycle timing.

	$Timing_{ik}$		
	(1)	(2)	(3)
Recurrent backer$_{-i,k}$	-0.025***		−0.026***
	(0.002)		(0.002)
Recurrent backer$_{-j,k}$		−0.002**	−0.002*
		(0.001)	(0.001)
Age	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)
First contribution value	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)
Campaign duration	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)
Campaign size	0.011***	0.011***	0.011***
	(0.000)	(0.000)	(0.000)
Entrepreneur experience	0.001***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)
Cash contribution	0.022***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)
Country of residence fixed effects	Yes	Yes	Yes
Category fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Observations	1,300,773	1,300,773	1,300,773
R^2	0.082	0.082	0.082

Note: The table presents OLS estimates of the effects of recursiveness on funding cycle timing. The dependent variable, $Timing_k$, 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*$_i$ 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, First contribution value, Campaign duration, Campaign size, Entrepreneur experience, and Cash contribution*. *Age* is the backer's age in years (in log), *First contribution value* 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. The sample contains all contributions made on the Ulule platform between July 5, 2010 and November 29, 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by backer. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

1 day before new backers (assuming an average campaign duration of 36 days).[13]

Combined, the results from Tables 4 and 5 are consistent with the idea that recurrent backers give rise to social learning about project existence and quality through their decisions to back sequentially different projects (Bikhchandani, Hirshleifer, and Welch 1998). Indeed, other backers can follow the lead of recurrent backers (because recurrent backers contribute earlier) and are interested in doing so (because recurrent backers more likely contribute to projects that will succeed). Recurrent backers provide informational value to other backers. Being observed by others as making more informed and independent pledge decisions, recurrent backers may thus generate social learning about projects on the platform. Importantly, this is the case regardless of whether backers are recurrent *within* a project or *across* the platform, suggesting that the learning initiated by recurrent backers acts as a transmission channel for both within-project dynamics and cross-project spillovers.

4 | Theoretical Framework

From the previous section, it appears that recurrent backers play a distinct role that may serve as a channel behind within-project dynamics and cross-project spillovers. However, the dynamic relationship between contributions to different projects is influenced by two additional factors: competition among entrepreneurs for limited funds and the platform's growth. The first factor, combined with new backers' tendency to follow trends, means that past contributions to one project can negatively affect current contributions to others. Meanwhile, the second factor leads to a positive correlation between past and current contributions, as both benefit from increased participation by backers.

We develop a theoretical framework to help us (i) disentangle the forces that shape the distribution of contributions on a CFP, both across projects and over time, and (ii) interpret the empirical results that we derive in Section 5. We sketch the framework here and send the details to Appendix A.

4.1 | Setting

We model the decisions of backers on a CFP to understand how contributions to some project on day $t-1$ affect contributions to this project and other projects on day t. For simplicity, we assume that each backer contributes to a single project and that contributions are fixed and normalized to 1. It follows that the total amount contributed to any project equals the number of backers to this project. We also assume that the platform proposes the same set of campaigns on days $t-1$ and t.[14] On the day of interest (day t), two types of backers choose the project they want to contribute to in the displayed set. They do so in sequence: recurrent backers—who already used the CFP on day $t-1$—make their decision before new backers—who join the CFP for the first time on day t.

At the start of day t, backers observe the contributions that the various projects attracted on the previous day. Let $y_{k,t-1}$ denote the number of contributions (and of backers) that project k ($k = 1, ..., K$) attracted on day $t-1$. Let also Y_{t-1} denote the total number of contributions on day $t-1$, that is, $Y_{t-1} = \sum_{k=1}^{K} y_{k,t-1}$.

4.2 | Decisions of Recurrent Backers

We assume that a share ρ, with $0 < \rho < 1$ of backers who used the CFP on day $t-1$, decide to use the CFP again on day t, thereby becoming recurrent backers. For simplicity, this share is constant across projects. We can thus see ρ as the rate of growth of the platform at the *intensive* margin. Based on the insights from Section 3, recurrent backers understand crowdfunding and this platform. This expertise enables them to evaluate the projects presented effectively and cost-efficiently. Consequently, recurrent backers are assumed to compare all available projects before deciding which one to support. Furthermore, their choice to fund a specific project is unaffected by the number of prior contributions to that project.

We denote by π_{ki} the "conversion rate" from k to i, that is, the probability that a recurrent backer who contributed to project k on day $t-1$ decides to contribute to project i on day t (with $0 \le \pi_{ki} \le 1$ for all $k, i = 1, ..., K$ and $\Sigma_i \pi_{ki} = 1$). The conversion rates can be seen as reflecting the average preferences of recurrent backers regarding successive contributions. We can then compute the total contributions from recurrent backers to project i on day t as:

$$y_{i,t}^{r} = \rho \sum_{k=1}^{K} \pi_{ki}\, y_{k,t-1}.$$

It is easily seen how changes in previous contributions affect the total contributions from recurrent backers:

$$\frac{\partial y_{i,t}^{r}}{\partial y_{k,t-1}} = \rho \pi_{ik} \quad \text{for } i, k = 1 \ldots K. \tag{2}$$

4.3 | Decisions of New Backers

A number Y_t of new backers decide to visit the CFP on day t. We observe that the two CFPs of our empirical analysis (like many other platforms) have been growing not only at the intensive margin (because of recurrent backers), but also at the *extensive* margin (because of increasing numbers of new backers). We posit therefore that $Y_t > Y_{t-1}$. In particular, we define $Y_t = (1+\mu)Y_{t-1}$, where $\mu > 0$ is the platform's rate of growth at the extensive margin.[15]

In contrast with recurrent backers, new backers have no previous experience with the platform (and, perhaps, with crowdfunding altogether). When they join the CFP, they know little about the projects on display. Because new backers are not able to evaluate their preferences for the displayed projects beforehand, we assume that they are randomly exposed to–for simplicity– some pair of projects (i, j). A new backer's decision to contribute to project i or to project j is then determined by their relative preference for the two projects (which they discover when examining them) and by comparing the number of contributions that the two projects collected thus far.[16] We further assume that new backers give more weight to past contributions made by recurrent backers, as they are recognized as more knowledgeable.

In Appendix A, we detail how a new backer chooses between the two projects they are exposed to. Aggregating the decisions across new backers, we can express the number of new backers contributing to project i on day t, $y_{i,t}^{n}$, as:

$$y_{i,t}^{n} = \frac{1+\mu}{\kappa} Y_{t-1} X_{i,t} \text{ with } X_{i,t} \equiv \sum_{k \ne i} \left(\frac{1}{2} + \frac{h(y_{i,t-1}) + H\left(y_{i,t}^{r}\right) - h(y_{k,t-1}) - H\left(y_{k,t}^{r}\right)}{2\tau_{ik}} \right), \tag{3}$$

where τ_{ij} is a measure of the degree of differentiation between projects i and j, $h(\cdot)$ measures the influence that the number of contributions to a given project in period $t-1$ has on the current decision to contribute to this project, and $H(\cdot)$ measures the same but for contributions of recurrent backers in period t.[17]

4.4 | Testable Predictions

We are now in a position to express the coefficients of interest for our empirical estimations. We start with *within-project dynamics*, that is, the impact that past contributions to some project have on current contributions to the same project. Within-project dynamics are measured by $\beta_1 \equiv \partial y_{i,t}^{r} / \partial y_{i,t-1} + \partial y_{i,t}^{n} / \partial y_{i,t-1}$. In Appendix A, we show that:

$$\beta_1 = \underbrace{(1+\mu)\frac{y_{i,t}^{n}}{Y_t}}_{EG} + \underbrace{\rho \pi_{ii}}_{IG_{ii}} + \underbrace{\frac{(1+\mu)Y_{t-1}}{KT_{-i}} h'(y_{i,t-1})}_{DH_i} + \underbrace{\frac{(1+\mu)\rho Y_{t-1}}{K(K-1)} \sum_{k \ne i} \frac{1}{\tau_{ik}} \left[\pi_{ii} H'\left(y_{i,t}^{r}\right) - \pi_{ik} H'\left(y_{k,t}^{r}\right) \right]}_{IH_i}. \tag{4}$$

We observe that within-project dynamics come from four distinct sources:

3. The third term, DH_i, is yet another *positive* term. It corresponds to a *direct herding effect*. Other things being equal, one additional contribution to project i on day $t-1$ places project i in a better position to gain contributions over all other contemporaneous projects on day t. For each alternative project $k \neq i$, this effect increases with the intensity of herding triggered by period $t-1$ backers – $h'(y_{i,t-1})$ – and decreases with the degree of differentiation between projects i and k – τ_{ik}. This effect generates additional contributions to project i at the rate of $(1+\mu)Y_{t-1}/\kappa$.
4. The sign of the fourth term, IH_i, is *ambiguous*. This term summarizes the influence of *indirect herding*, that is, the fact that new backers follow recurrent backers, whose contributions on day t depend on contributions on day $t-1$. This term is equal to zero in the fully symmetric case (i.e., if $y_{i,t-1} = y_{j,t-1}$ and $\pi_{ij} = \pi_{ji}$ for all $i, j = 1 \ldots k$). It is more likely to be positive if, compared to the other projects, project i (i) attracted relatively more contributions on day $t-1$ and (ii) induces relatively more recurent backers to convert.[18] The indirect herding effect has the same magnitude as the direct herding effect.

We turn now to *cross-project spillovers*, that is, the impact that past contributions to some project z ($y_{z,t-1}$) exert on current contributions to some *other* project i ($y_{i,t} = y^r_{i,t} + y^n_{i,t}$). In Appendix A, we show that cross-project spillovers can also be decomposed as the sum of four terms:

$$\frac{\partial y_{i,t}}{\partial y_{z,t-1}} = \underbrace{(1+\mu)\frac{y^n_{i,t}}{Y_t}}_{EG} + \underbrace{\rho\pi_{zi}}_{IG_{zi}} - \underbrace{\frac{(1+\mu)Y_{t-1}}{K(K-1)\tau_{iz}}h'(y_{z,t-1})}_{DH_z} + \underbrace{\frac{(1+\mu)\rho Y_{t-1}}{K(K-1)}\sum_{k\neq i}\frac{1}{\tau_{ik}}\left[\pi_{iz}H'\left(y^r_{i,t}\right) - \pi_{kz}H'\left(y^r_{k,t}\right)\right]}_{IH_z}. \quad (5)$$

The main difference between Expressions (4) and (5) comes from the third term. Whereas the direct herding effect is positive for the within-project dynamics, it is *negative* for cross-projects spillovers: $DH_z < 0$. Other things being equal, one additional contribution to project z on day $t-1$ convinces more new backers to contribute to project z on day t because of direct herding. This drives contributions away from project i at the rate of Y_t/κ. As expected, the competition that project z exerts on project i is weaker if the two projects are perceived as more differentiated. Hence, DH_z is less negative if τ_{iz} is larger. Otherwise, the other factors (μ, Y_{t-1}, and K) affect DH_i and DH_z in the same way.

As for the three other terms, external growth (term 1) has the exact same impact on within-project dynamics and cross-project spillovers. The impacts of internal growth (term 2) and of indirect herding (term 4) have the same form but are mediated by different conversion probabilities. For instance, the impact of internal growth depends on π_{ii} for within-project dynamics and π_{zi} for cross-project spillovers (i.e., the probability that recurrent backers who backed project z on day $t-1$ decide to back project i on day t).

4.5 | Expectations Regarding Coefficients

The decomposition of the within-project dynamics indicates that *we can expect β_1 to be positive*. To reverse this prediction, the indirect herding effect should be sufficiently negative to outweigh the other three positive effects, which seems very unlikely.

Predicting the sign of the cross-project spillovers is much harder. Our theoretical framework allows us, however, to state that *cross-project spillovers are more likely to be positive the stronger the platform's growth (at the intensive and extensive margins) and the more the projects under review are differentiated*. To refine these predictions, we further simplify the framework. For our empirical analysis, we compare project i to two distinct subsets of projects: the projects that belong to the same category as project i and the projects belonging to other categories. We denote these two subsets, respectively, as K_{-i} and K_{-j}, with $K = \{i\} \cup K_{-i} \cup K_{-j}$. Considering projects as symmetric within each subset, we can set $\tau_{ik} \equiv \tau_{-i}$ and $\pi_{ki} = \pi_{ik} = \pi_{-i}$ for projects $k \in K_{-i}$, $\tau_{ik} = \tau_{-j}$ and $\pi_{ki} = \pi_{ik} = \pi_{-j}$ for $k \in K_{-j}$, and $\pi_{kk} \equiv \pi$ for all k. As pairs of projects belonging to different categories are more differentiated in the eyes of new backers than pairs of projects belonging to the same category, we can posit that $\tau_{-j} > \tau_{-i}$. Regarding the transition probabilities, Supporting Information S1: Table OA1 suggests the following relationships: $\pi > \pi_{-i} > \pi_{-j}$, that is, recurrent backers are more likely to back again the same project than a project belonging to the same category or, worse, a project belonging to another category.

Under these assumptions, we can derive two versions of Expression (5), according to whether project z belongs to K_{-i} or K_{-j}; we write:

$$\beta_2 \equiv \frac{\partial y_{i,t}}{\partial y_{z,t-1}} \quad \text{if } z \in K_{-i} \quad \text{and} \quad \beta_3 \equiv \frac{\partial y_{i,t}}{\partial y_{z,t-1}} \quad \text{if } z \in K_{-j}.$$

Developing these two expressions with $v \in K_{-i}$ and $w \in K_{-j}$, we find:

$$\beta_3 - \beta_2 = \frac{(1+\mu)Y_{t-1}}{K(K-1)}\left(\frac{h'(y_{w,t-1})}{\tau_{-i}} - \frac{h'(y_{v,t-1})}{\tau_{-j}}\right) - \rho(\pi_{-i} - \pi_{-j}).$$

To facilitate the comparison, suppose that the two projects v and w received the same number of contributions on day $t-1$: $y_{v,t-1} = y_{w,t-1} = y_{,t-1}$. Then,

$$\beta_3 > \beta_2 \Leftrightarrow \frac{\tau_{-j} - \tau_{-i}}{\pi_{-i} - \pi_{-j}} > \frac{\rho K(K-1)\tau_{-i}\tau_{-j}}{(1+\mu)Y_{t-1}h'(y_{,t-1})}.$$

Hence, our model suggests that β_3 is more likely to be larger than β_2 if categories of projects differ more in terms of differentiation (as perceived by new backers) than in terms of conversion rates (for recurrent backers), that is, if the ratio $(\tau_{-j} - \tau_{-i})/(\pi_{-i} - \pi_{-j})$ is large enough.

5 | Empirical Results

This section provides our empirical results on within-dynamics and spillovers, as well as on the role of recurrent backers as a transmission channel.

5.1 | Within-Project Dynamics and Cross-Project Spillovers

We estimate the following specification derived from our theoretical framework:

$$y_{it} = \alpha_i + \alpha_t + \beta_1 Y_{i,t-1} + \beta_2 Y_{-i,t-1} + \beta_3 Y_{-j,t-1} + \gamma \boldsymbol{X}_{it} + \varepsilon_{it}, \quad (6)$$

where 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);[19] $Y_{i,t-1}$ 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. The vector of control variables takes into account time-varying project-level characteristics (namely, *Competing projects*$_i$, *Financing progress, Popular*).[20] The coefficient of interest, β_1, measures within-project dynamics on the number of contributions received by a particular project, while the coefficients of interest, β_2 and β_3, measure cross-project spillovers. 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.[21] The most recent contributions thus provide the next backers with the most relevant information. Astebro et al. (2024) show that accumulated contributions have any additional marginal impact on the following contributions since (rational) backers consider all prior funding history encapsulated by the most recent contribution. However, in Section 5.2, we relax this assumption and use past contributions over various time windows.

Table 6 reports the coefficients of fixed-effect regression models derived from specification 6. We first estimate within-project dynamics and cross-project spillovers separately. In column 1, we estimate within-project dynamics besides the full set of control variables and fixed effects. The coefficient of interest (β_1 in specification 6 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 spillovers instead. Column 2 estimates cross-project spillovers within categories, while column 3 describes cross-project spillovers across categories. The coefficients of interest, 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-project dynamics and cross-project spillovers together. The results are unchanged: β_1, β_2, and β_3 are positive and significant. Interestingly, we note that β_3 is consistently larger than β_2, which indicates that new backers see projects as much more differentiated across categories than within categories.[22] Since the contributions made are highly conditional on current funding status (Mollick 2014; Strausz 2017), we also restrict our sample in column 5 to the campaign period during which the funding goal of projects is not (yet) met. In column 6, we go on to investigate the differential funding dynamics across each of the 15 Ulule categories. Again, the estimates of the coefficients of interest are positive and significant.

Across columns 1–6, the coefficients of within-project dynamics and cross-project spillovers are positive, always statistically significant at the 1% level, and have similar magnitudes. The respective contributions of these dynamics and spillovers have meaningful economic consequences. Using results from column 4, a doubling (a 100% increase) in the number of contributions on project i results in a 16.07% increase in the number of contributions the day after on the same project i while holding all other variables constant.[23] This result confirms the findings of prior works (cited at the outset) similarly documenting within-project dynamics. However, the novelty here is the identification of sizeable cross-project spillovers. Specifically, using again the results from column 4, a doubling in the number of contributions within (across) categories on a particular day subsequently leads to a 1.12% (3.81%) increase in the number of contributions on a project.[24] The results on cross-project spillovers from column 5, focusing on campaign periods in which projects are not fully funded, yield slightly higher economic magnitudes.

It appears that cross-project spillovers across categories are, on average, economically larger than within categories. To understand this result, we refer to the theoretical framework outlined in Section 4. It is important to recall that four effects influence cross-project spillovers: three of these effects are positive (external growth, internal growth, and indirect herding), while the fourth effect (direct herding) is negative. Since both estimated coefficients are positive, it indicates that the positive

TABLE 6 | Within-project dynamics and cross-project spillovers.

	(1)	(2)	(3)	(4)	(5)	(6)
Contributions$_i$	0.217***			0.215***	0.165***	0.215***
	(0.002)			(0.002)	(0.002)	(0.002)
Contributions$_{-i}$		0.033***		0.016***	0.017***	
		(0.002)		(0.002)	(0.002)	
Contributions$_{-j}$			0.089***	0.054***	0.055***	
			(0.003)	(0.003)	(0.003)	
Contributions$_{Art\&Photo}$						0.011***
						(0.001)
Contributions$_{Charities\&Citizen}$						0.011***
						(0.002)
Contributions$_{Childhood\&Education}$						0.002
						(0.001)
Contributions$_{Comics}$						0.003***
						(0.001)
Contributions$_{Crafts\&Food}$						0.007***
						(0.001)
Contributions$_{Fashion\&Design}$						0.002*
						(0.001)
Contributions$_{Film\&Video}$						0.006***
						(0.002)
Contributions$_{Games}$						0.001
						(0.001)
Contributions$_{Heritage}$						0.014***
						(0.002)
Contributions$_{Music}$						0.002*
						(0.001)
Contributions$_{Other}$						0.005***
						(0.001)
Contributions$_{Publishing\&Journalism}$						0.007***
						(0.001)
Contributions$_{Sports}$						0.006***
						(0.002)
Contributions$_{Stage}$						0.015***
						(0.002)
Contributions$_{Technology}$						0.005***
						(0.001)
Competing projects$_i$	0.004	−0.034***	−0.025***	−0.032***	−0.025***	−0.031***
	(0.007)	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)
Financing progress	−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	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

(Continues)

TABLE 6 | (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
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

Note: This table presents fixed-effects estimates of the within-project dynamics and cross-project spillovers 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 spillovers 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 spillovers across categories. Control variables include *Competing projects*$_i$, *Financing progress, Popular*. *Competing projects*$_i$ is the number of projects within category i (in log). Financing progress is the ratio of the amount raised to targeted goal, *Popular* is a dummy variable equal to 1 if the project is among the eight 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 July 5, 2010 and November 29, 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by project. Symbols *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE 7 | Within-project dynamics and cross-project spillovers: Alternative sets of time fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)
$Contributions_i$	0.247***	0.204***	0.246***	0.203***	0.217***	0.168***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$Contributions_{-i}$	0.005**	0.007***	0.016***	0.016***	0.018***	0.019***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
$Contributions_{-j}$	0.010	0.019	0.055***	0.059***	0.047***	0.050***
	(0.013)	(0.014)	(0.003)	(0.003)	(0.002)	(0.002)
$Competingprojects_i$	−0.011	−0.015*	−0.002	−0.001	−0.018**	−0.012
	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)
Financingprogress	−0.249***	−0.294***	−0.222***	−0.279***	−0.157***	−0.130***
	(0.007)	(0.010)	(0.005)	(0.007)	(0.006)	(0.008)
Popular	1.239***	1.155***	1.246***	1.162***	1.210***	1.121***
	(0.010)	(0.012)	(0.009)	(0.011)	(0.010)	(0.012)
Project fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Calendar day fixed effects	Yes	Yes	No	No	No	No
Category × week-month-year fixed effects	No	No	Yes	Yes	No	No
Category × funding cycle day fxed effects	No	No	No	No	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

Note: This table presents robust fixed-effects estimates of the within-project dynamics and cross-project spillovers on the number of contributions received by projects over their funding cycle. Depending on the columns, the sets of time fixed effects differ from Table 6. 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 spillovers 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 spillovers across categories. Control variables include *Competing projects*$_i$, *Financing progress, Popular*. *Competing projects*$_i$ is the number of projects within category i (in log). *Financing progress* 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. Odd-numbered columns include all observations from all projects, while even-numbered columns exclude 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.

effects are stronger than the negative one. When we compare projects in different categories to those within the same category, we observe a decrease in the strength of all effects (except the external growth effect, which remains unchanged). On the one hand, the negative impact of the direct herding effect diminishes because projects in different categories tend to be more differentiated, leading to reduced competition among them. On the other hand, the positive influences of internal growth and indirect herding are less pronounced, as recurrent backers are less inclined to contribute to projects in a different category compared to the category of their initial contribution. Ultimately, our findings suggest that the decreased competition among categories outweighs the reduced likelihood of recurrent backers engaging across categories, explaining why cross-project spillovers are stronger across categories than within a category.

In column 6, we explore this further by examining the spillover effects of each category individually. The results indicate that some categories indeed generate relatively larger cross-project spillovers than other categories. For example, the categories *Heritage* and *Art & Photo*, with large and significant coefficients, exhibit more pronounced cross-project spillovers 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: by attracting a crowd of specialized backers, this category does generate cross-project spillovers but only within the category itself. In addition, in Table 7, we investigate whether other time trends across categories influence our findings on cross-project spillovers. In odd-numbered columns, we examine the entire campaign (as in column 4 of Table 6), while in even-numbered columns (as in column 5 of Table 6), we only focus on the campaign periods during which projects are not yet fully funded. The inclusion of category-fixed effects, interacted with various sets of time-fixed effects, yields similar conclusions about cross-project spillovers.

The evidence from control variables throughout the specifications shows that the number of active projects within categories are negatively associated with 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 (as our theoretical framework indicates with a negative competition effect). The other control variables suggest that the number of contributions received by projects reduces as the campaign approaches its funding goal, while projects being part of the ones featured on the first page of Ulule appear to generate more contributions.

Since many projects do not achieve any funding on a given day, we take the log of 1 plus the number of contributions to retain observations with zero-valued outcomes. However, linear regressions where the dependent variable is the log of 1 plus the count outcome may produce the opposite sign of the true relationship being estimated (Cohn, Liu, and Wardlaw 2022). An alternative to estimating our specification 6 is, therefore, to rely on Poisson regressions as they can accommodate count outcomes with a mass of values at zero. Poisson regressions indeed produce consistent and reasonably efficient estimates under standard exogeneity conditions, even with multiple levels of fixed effects. Table 8 reports the coefficients of Poisson regression models. In columns 1–4, we consider both within-project dynamics and cross-project spillovers with different combinations of fixed effects and control variables. Column 3 is the same specification as the one in column 4 of Table 6 and column 4 is the same as in column 5 of Table 6, limiting the sample to the campaign period during which the funding goal is not yet met. As we can observe, the Poisson regressions confirm our initial findings. Since our findings do not appear to be driven by the linearity of the model, we will report the linear estimation results in the remaining analysis.

Collectively, the results in this section strongly characterize the importance of within-project dynamics and cross-project spillovers in crowdfunding. We now evaluate their robustness further.

5.2 | Robustness Tests

We first probe the robustness of our results to alternative definitions of the variables of interest.[25] We focus on the volume of contributions (i.e., €-amount) instead of the number of contributions. This alternative definition is helpful for two reasons. First, it is unclear whether funding dynamics and spillovers only operate through an increase in the number of backers per project or, also, 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 Supporting Information S1: Table OA3, we mirror the specifications of columns 1–6 in Table 6 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 funding dynamics may capture short-term liquidity fluctuations rather than category-wide (platform-wide) dynamics. To assuage this concern, we re-estimate within-project dynamics and cross-project spillovers using the rolling average of past contributions over different time windows instead of the contributions of the past day. Supporting Information S1: Table OA4 mirrors the specification of column 4 in Table 6 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.[26] Our conclusions are unchanged.

A core finding in the crowdfunding literature is that the entrepreneur's immediate circle is critical at the beginning of a campaign for encouraging further contributions (e.g., Mollick 2014; Agrawal, Catalini, and Goldfarb 2015). Backers from this immediate circle typically contribute early in the campaign and are likely to make repeat contributions to the project. To ensure that our results are not driven by these early-campaign dynamics, we re-estimate the specification of column 4 in Table 6 by excluding the first 5 days of each campaign. The results in Table AO5 confirm our initial findings.

Last, in Supporting Information S1: Table OA6, we test the replicability of our results using data from KKBB. We obtained

TABLE 8 | Within-project dynamics and cross-project spillovers: Poisson regressions.

	(1)	(2)	(3)	(4)
Contributions$_i$	0.0017***	0.0010***	0.0009***	0.0019**
	(0.0002)	(0.0002)	(0.0002)	(0.0009)
Contributions$_{-i}$	0.0003***	0.0001**	0.0001***	0.0001***
	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Contributions$_{-j}$	0.0003***	0.0001***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Competing projects$_i$			−0.0023***	−0.0009*
			(0.0009)	(0.0005)
Financing progress			−0.4898***	−0.5718**-*
			(0.0325)	(0.0305)
Popular			1.7781***	1.6392***
			(0.0143)	(0.0180)
Project fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	No	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes
Day of week fixed effects	No	Yes	Yes	Yes
Funding cycle day fixed effects	No	Yes	Yes	Yes
Observations	814,960	814,700	814,700	681,087
Projects	23,022	22,761	22,761	22,311
Pseudo R^2	0.0409	0.3994	0.4650	0,3845

Note: This table presents Poisson estimates of the within-project dynamics and cross-project spillovers 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. 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 and captures cross-project spillovers 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 and captures cross-project spillovers across categories. Some specifications include control variables, namely Competing projects$_i$, *Financing progress, Popular*. Competing projects$_i$ is the number of projects within category *i*. *Financing progress* is the ratio of the amount raised to targeted goal, Popular is a dummy variable equal to 1 if the project is among the eight projects being featured on the first page of Ulule website during a day and 0 otherwise. All columns implement Poisson pseudomaximum likelihood regressions with (multiple levels of) fixed effects as described by Correia, Guimarães, and Zylkin (2020). Columns 1–3 include all observations from all projects, while column 4 excludes the observations of projects when their target goal is reached. The sample contains all projects posted on the Ulule platform between July 5, 2010 and November 29, 2016. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by project. Symbols *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

from KKBB similar granular data as from Ulule, which also allows us to trace the exact timing and amount pledged by all backers between 2010 and 2015. KKBB categories have been redefined several times during the period of investigation, which prevented us from distinguishing between cross-project spillovers within and across categories.[27]

In Panel A of Supporting Information S1: Table OA6, we estimate within-project dynamics and cross-project spillovers separately (columns 1 and 2) and together (column 3).[28] As can be seen, the coefficients of within-project dynamics and cross-project spillovers are positive, always statistically significant at the 1% level, except in column 3 where the coefficient of cross-project spillovers turns out insignificant. Regarding the economic significance of the results, we find that a doubling in the number of contributions within (across) projects on a particular day subsequently leads to a 17.61% (0.84%) increase in the number of contributions on a project (using the results from columns 1 and 2). Economically, these results on KKBB are very similar to those on Ulule.

This similarity may seem surprising at first glance. However, we can refer to our theoretical framework to offer some explanation. Let us focus here on β_2 (a similar argument can be made for β_3). To fix ideas, assume that the herding functions are linear: $h(y_{j,t-1}) = h \times y_{j,t-1}$ (so that $h'(y_{j,t-1}) = h$) and $H\left(y^r_{j,t}\right) = H \times y^r_{j,t}$ (so that $H'\left(y^r_{j,t}\right) = H$), with $H > h$. Then, expression (5) becomes:

$$\beta_2 = \rho\pi_{-i} + (1+\mu)\left[\frac{y^n_{i,t}}{Y_t} - \frac{hY_{t-1}}{K(K-1)\tau_{-i}} + \frac{H\rho Y_{t-1}}{K(K-1)} \sum_{k\neq i} \frac{\pi_{iz} - \pi_{kz}}{\tau_{ik}}\right].$$

We observe in our data that Ulule (superscript u) dominates KKBB (superscript k) regarding (i) the share of recurrent backers ($\rho^u > \rho^k$), the external growth rate ($\mu^u > \mu^k$), and volume of contributions ($Y^u > Y^k$, $y^u > y^k$, $y^{nu} > y^{nk}$, and $y^{ru} > y^{rk}$).[29] As for the other variables of interest (π, π_{-i}, τ_{-i}, K,

h, and H), let us assume that they do not differ significantly across platforms. We see that the difference in size between the two platforms exert opposing forces on β_2: the first term drives β_2^u to be larger than β_2^k but the second bracketed term drives β_2^u to be *smaller* than β_2^k. Our estimates show that these two forces seem to balance in the present case.

5.3 | Cross-Project Spillovers Generated By Fast Starters

The systematic examination of funding dynamics in the previous subsections revealed the existence of significant spillovers between projects, which deserve further attention. Here, we sharpen the identification of cross-project spillovers using plausibly exogenous variation from "fast starters," that is, campaigns generating a vast number of contributions during their *first day*. This allows us to test our prediction with more precision.

Our primary identifying assumption is that the identity of fast starters is largely unexpected by backers, entrepreneurs, or platform managers and, thereby, is plausibly exogenous in our campaign sample. In Supporting Information S1: Table OA7, we report statistics and information consistent with this assumption. First, we find no indication in the media that campaigns with a fast start garnered attention on Factiva in the weeks or months leading up to their launch, suggesting a lack of prelaunch hype (see columns on Factiva search outcome). Second, we observe that the entrepreneur's immediate circle (see last column) or backers making abnormal contributions on the day a campaign experiences a fast start (see penultimate column) cannot plausibly account for potential manipulation by certain backers (e.g., Crosetto and Regner 2018; Astebro and Penalva 2023). Indeed, these backers represent a very small fraction of backers contributing to a fast-start campaign.[30]

We use a difference-in-differences setting to estimate cross-project spillovers. Specifically, we estimate the following model:

$$y_{ijt} = \alpha_i + \alpha_t + \beta Fast\ start_{jt} + \boldsymbol{\gamma X}_{it} + \varepsilon_{ijt}, \tag{7}$$

where 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 (0 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).

The analysis presented in Table 9 yields two main results that confirm our prediction about the presence of spillover effects. First,

TABLE 9 | Cross-project spillovers around fast starts.

	>200		>500	
	(1)	**(2)**	**(3)**	**(4)**
$Fast\ start_t$	0.015***		0.029***	
	(0.005)		(0.008)	
$Fast\ start_j$ [1]		0.040**		0.048**
		(0.016)		(0.024)
$Fast\ start_{-j}$ [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

Note: The 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, $Fast\ start_{j(-j)}$ 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 spillovers of a project's fast start (within and/or across categories). Supporting Information S1: Table OA5 reports the projects that experienced an unexpected fast start. Control variables included in the estimations but untabulated for brevity are $Contributions_i$ (lagged), $Competing\ projects_i$, Financing progress (lagged), *Popular* and are defined as in Table 6. The sample contains all projects (*except the fast starters themselves*) posted on the Ulule platform between July 5, 2010 and November 29, 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.

when a project experiences a fast start, all other contemporaneous projects on the platform benefit from it. Specifically, in odd-numbered columns of Table 9, we estimate the cross-project spillovers generated on the CFP by fast starters. 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. We can see that the coefficient of interest is always positive and significant at the 1% level. Fast starters are not included in the sample to make

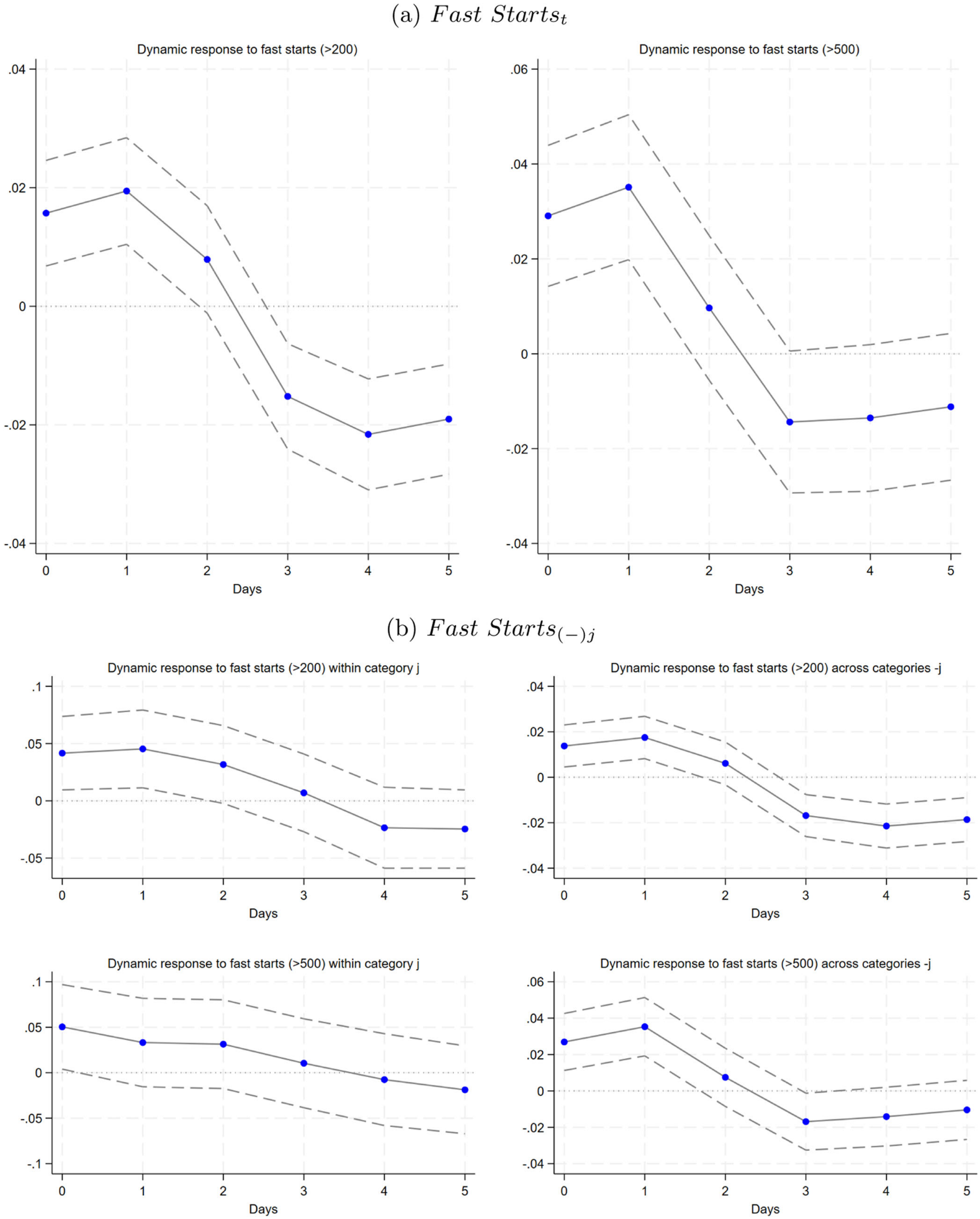


FIGURE 2 | Legend on next page.

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, the impact of fast starters is more pronounced on projects within their own category (i.e., β in specification 7). In even-numbered columns, we present the difference-in-differences estimates of the effect of fast starters.[31] 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). 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 Supporting Information S1: Table OA8).

These results indicate that fast starters generate cross-project spillovers on the same day they occur on the platform. However, these spillovers may spread more slowly, with longer and more uncertain lags. Therefore, we also estimate the dynamic response of the number of contributions received by projects to the occurrence of fast starters. To trace out the dynamic impact of fast starters' activity on the number of daily contributions projects get, we use local projections by estimating a model similar to Equation (7) for several time horizons (Jordà 2005). Figure 2 exhibits the local projections, which are consistent with the baseline results of Table 9 and complement them by illustrating their dynamic effects. Figure 2a shows a contemporaneous increase in the average number of daily contributions received by all projects on the platform in response to the occurrence of fast starters (either of >200 or >500 contributions). Interestingly, fast starters continue to generate positive cross-project spillovers for the next 2 days, after which the effect decreases and can even become negative. Panel B indicates that positive cross-project spillovers within categories persist slightly longer (by 1 day) than those across categories.

5.4 | Recurrent Backers as a Transmission Channel

So far, we have considered backers to be a homogeneous group of individuals, irrespective of whether they are new or recurrent on the CFP. As argued in Sections 3 and 4, recurrent backers have accumulated experience and, thereby, can make more informed decisions than new backers. Arguably, more information can be inferred from observing the behavior of more experienced decision-makers. Therefore, new—inexperienced—backers can learn from the decisions of recurrent backers, which implies that recurrent backers have the potential to act as an important transmission channel for cross-project spillovers.[32]

To explore transmission channel behind cross-project spillovers, we now show the extent to which recurrent backers play a different role than new backers. Table 10 displays the results. In Panel A, we estimate funding dynamics and spillovers like in Table 6, 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 (see Figure 1). In columns 1 to 3, we examine within-project dynamics and cross-project spillovers separately, while in column 4 we examine them together.[33] 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 0; we can thus reject the hypothesis of no differences between new backers and recurrent backers. Hence, new and recurrent backers produce distinct effects on funding dynamics and spillovers.

In Panel B, we estimate cross-project spillovers 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 generate significantly larger cross-project spillovers when they count relatively more contributions from recurrent backers than from new 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 and outside their category (using estimates from column 2).

Moreover, we verify the robustness of our results in this subsection using instead the volume of contributions as dependent variables of interest (see Supporting Information S1: Table OA9). We do not find any evidence that alters our conclusions on recurrent backers. The results in this subsection are important as they indicate that recurrent backers play a distinct role from new backers in shaping within-project dynamics and also cross-project spillovers.

FIGURE 2 | Dynamic response to fast starts. *Note:* The figure presents the dynamic response of the number of contributions received by projects to the introduction of fast starts, estimated using local projections. That is, for each horizon h, we estimate the following model: $y_{i,j,t+h} = \alpha_i + \alpha_t + \beta^h \text{Fast start}_{jt} + \boldsymbol{\gamma}^{\boldsymbol{h}'} \boldsymbol{X}_{it} + \varepsilon_{ijt}$. The superscripts or subscripts h are the horizon (a day t). All variables and parameters are the same as in Equation (7). The sample contains all projects (except the fast starters themselves) posted on the Ulule platform between July 5, 2010 and November 29, 2016. Each point represents the point estimate of the coefficient of *Fast start* in a specific lead day ("horizon h"). The dashed line represents 95% confidence intervals using standard errors clustered by projects. Panel a shows the dynamic response to faster starts (respectively, with more than >200 and >500 contributions) across categories. Panel b shows the dynamic response to faster starts both within their category and across categories. Both panels mirror the tests in Table 9. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 10 | New backers versus recurrent backers.

Panel A: Within-project dynamics and cross-project spillovers				
	(1)	**(2)**	**(3)**	**(4)**
New contributions$_i$ [1]	0.197***			0.195***
	(0.002)			(0.002)
Recurrent contributions$_i$ [2]	0.156***			0.154***
	(0.002)			(0.002)
New contributions$_{-i}$ [1]		0.028***		0.015***
		(0.002)		(0.002)
Recurrent contributions$_{-i}$ [2]		0.008***		0.002*
		(0.002)		(0.001)
New contributions$_{-j}$ [1]			0.074***	0.045***
			(0.004)	(0.003)
Recurrent contributions$_{-j}$ [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 spillovers around fast starts				
	>200		**>500**	
	(1)	**(2)**	**(3)**	**(4)**
New fast start$_t$	−0.007		−0.020	
	(0.007)		(0.014)	
New fast start$_j$ [1]		−0.023		0.033
		(0.027)		(0.046)
New fast start$_{-j}$ [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$_j$ [3]		0.074**		0.057
		(0.032)		(0.044)
Recurrent fast start$_{-j}$ [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

(Continues)

TABLE 10 | (Continued)

Panel B: Cross-project spillovers around fast starts	>200		>500	
	(1)	(2)	(3)	(4)
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

Note: The table presents estimates of the within-project dynamics and cross-project spillovers 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 6 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 9 but differentiates new backers from recurrent backers. All the variables are defined as in Tables 6 and 9. The sample contains all projects posted on the Ulule platform between July 5, 2010 and November 29, 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.

6 | Implications

Our findings paint a positive role of recurrent backers in stimulating funding dynamics within projects but also in generating positive spillovers across projects. We argue that this is because recurrent backers induce social learning. Some questions naturally arise: To what extent does the behavior of recurrent backers reverberate at the platform level? In particular, do recurrent backers contribute to amplifying the total number of contributions generated over time? If so, do they affect competition between reward-based CFPs? It is beyond the scope of our paper to address these questions empirically. However, our findings have implications for CFP growth and competition that we discuss below.

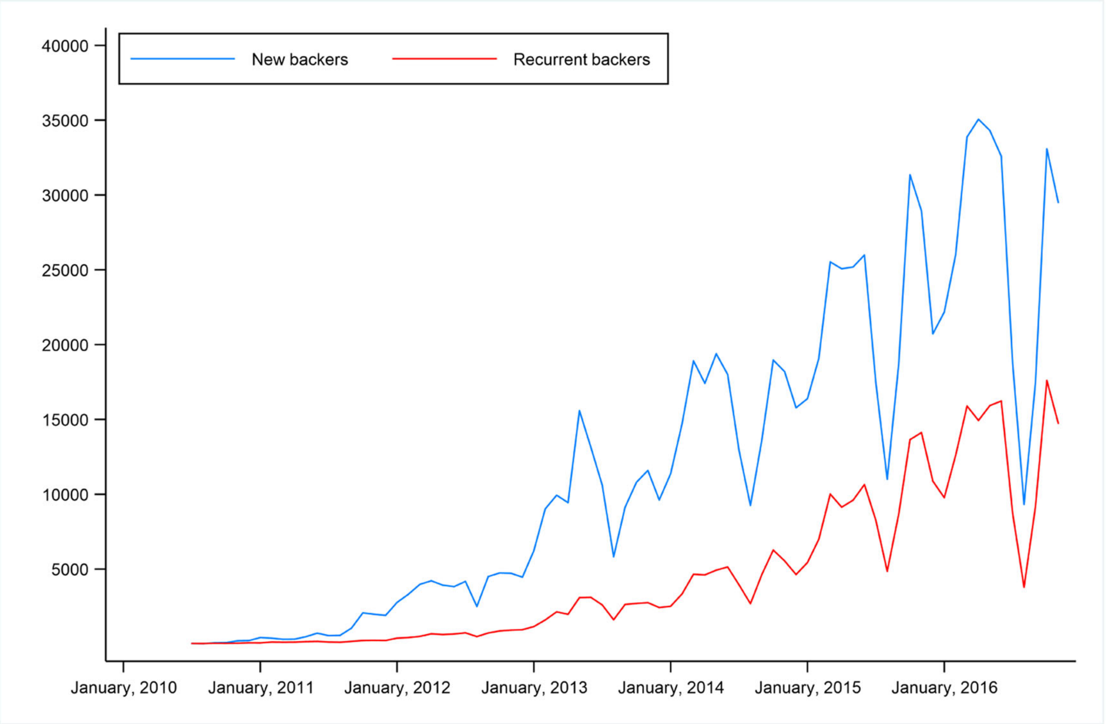
To shed light on these questions, we look at the evolution of the share of recurrent backers on both Ulule and KKBB platforms. Figure 3 exhibits the total monthly number of contributions made by project backers on Ulule (Panel a) and KKBB (Panel b) from the inception of the platforms onwards. Both platforms experienced an evident rise in the number of contributions over time, with the bulk of these contributions made by new backers (blue line). The number of recurrent backers (red line) also increases over the period, though at a different pace across the two platforms. Ulule has a higher share of recurrent backers than KKBB. Although both CFPs were launched around the same period, what we see in the data is the higher rate at which the number of recurrent backers per project grows over the sample period: the compound annual growth rate (untabulated) over the sample period is 33.1% and 3.0% for Ulule and KKBB, respectively. Figure 4 presents 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. This gap is especially marked in the most recent year. Combined, Figures 3 and 4 suggest that recurrent backers partly account for the diverging growth trajectories of Ulule and KKBB. They also suggest that Ulule would have better succeeded at retaining recurrent backers since its inception.

Although the role of recurrent backers in initiating social learning provides a compelling reason for the growth of Ulule and KKBB, other factors may also be at work. Indeed, the number of contributions per project may further increase as network effects kick in (Belleflamme, Omrani, and Peitz 2015). As our theoretical framework shows, the platform's growth at the extensive margin also plays an important role. Some backers are incentivized to contribute to a given project if other backers contribute as well (same-side network effects through, e.g., word-of-mouth) or if more entrepreneurs are present and thus more projects are listed (cross-side network effects). Network effects may arise even when all backers have full information about the existence or quality of the project (i.e., when social learning has ceased). Network effects are thus unlikely to wear off, amplifying funding dynamics and spillovers even after any hidden information about projects has been learned. Funding dynamics and spillovers, as well as the growth path of CFPs, also depend on network effects.[34] 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 is suggestive that the French market for reward-based crowdfunding is following such a path.

7 | Conclusion

This paper contributes to the literature on crowdfunding by providing a theoretical framework and empirical estimates for positive cross-project spillovers, that is, the fact that current contributions to a given project increase with past contributions to other projects displayed contemporaneously on a CFP. Our estimates, based on unique data from two leading European reward-based CFPs (Ulule and KKBB), show that these spillovers are relatively large, as they imply approximately a 4% increase in the daily project contributions. We also elicit the critical role played by recurrent backers in generating these

(a) Ulule



(b) KKBB

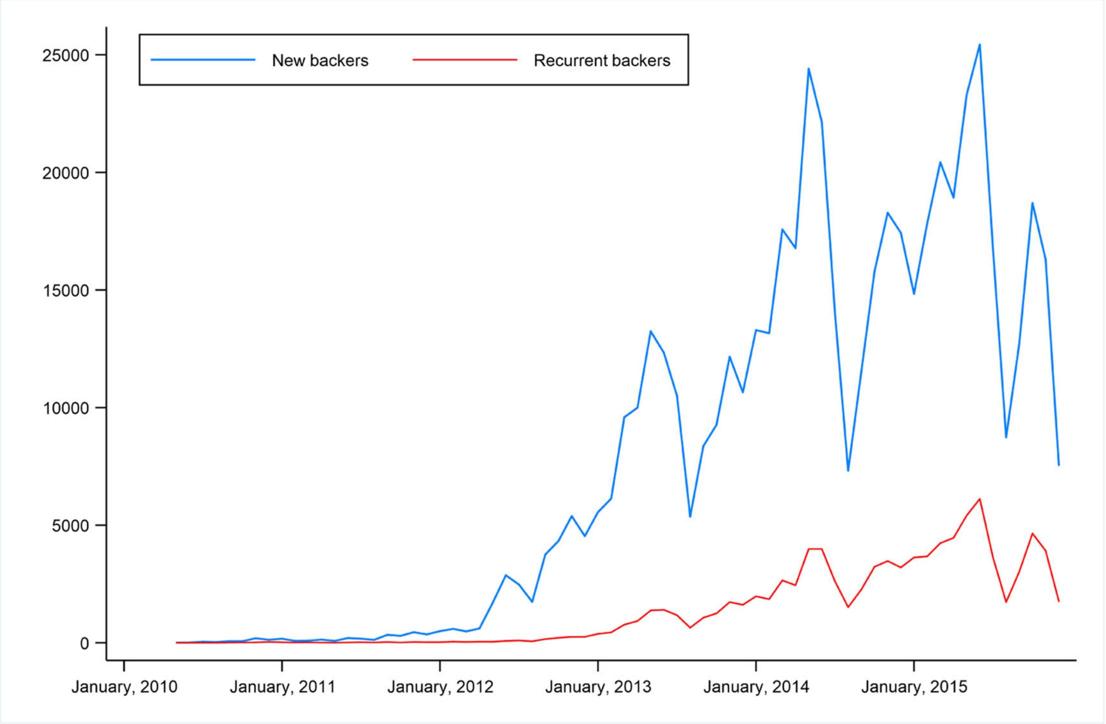


FIGURE 3 | Number of backers over time. *Note:* The figure presents the evolution of the number of both new and recurrent backers visiting Ulule between July 5, 2010 and November 29, 2016 (Panel a) and visiting KKBB between May, 23 2010 and December, 31 2015 (Panel b). The y-axis is the number of backers (new and recurrent) and the x-axis is the time (monthly). [Color figure can be viewed at wileyonlinelibrary.com]

spillovers. On the one hand, the repeated contributions of recurrent backers are a source of internal growth that complements the platform's external growth to raise the total amount of contributions. On the other hand, recurrent backers make more informed and independent pledge decisions, which induces other—less experienced—backers to follow their lead and contribute to projects they may not have considered otherwise (a form of social learning). Incidentally, the analysis also confirms

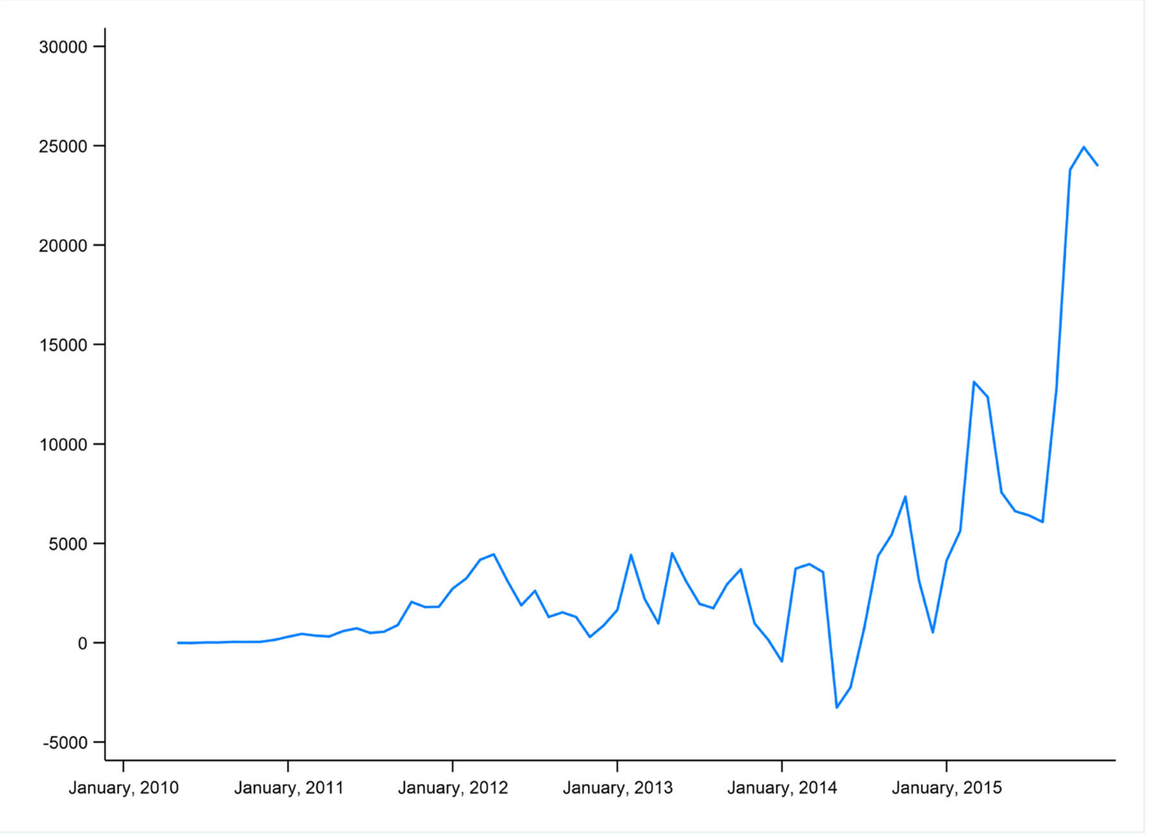


FIGURE 4 | Ulule–KKBB gap over time. *Note:* The figure presents the evolution of the contribution gap between Ulule and KKBB. The y-axis is the difference in the total number of contributions between Ulule and KKBB and the x-axis is the time (monthly). [Color figure can be viewed at wileyonlinelibrary.com]

the existence (already documented in prior work) of within-project dynamics: current contributions to a given project increase with past contributions to this project. Finally, the findings in this paper provide novel (though suggestive) insights regarding the increased concentration observed in most crowdfunding markets. In particular, the evolution of the number of recurrent backers on the two platforms in our sample plausibly accounts for their diverging growth trajectories in the past decade. This suggests that recurrent backers, by boosting funding dynamics within projects and generating positive spillovers across projects, are a source of competitive advantage for CFPs.

Even if our empirical study focuses on reward-based crowdfunding, we believe that this paper has a broader scope. First, reward-based crowdfunding is important to consider in its own right as it represents a sizeable channel for raising money for early-stage projects, especially in creativity-based industries. Second, from a research point of view, reward-based CFPs provide an ideal setting for analyzing learning in funding decisions because they attract a vast population of backers who can observe (at least in Ulule and KKBB) the contributions of others within and across projects. Third, our theoretical framework applies equally to other forms of crowdfunding (equity-, loan-, or donation-based). Fourth, reward-based CFPs share essential characteristics with other digital platforms, such as marketplace lending platforms, token-based platforms, and e-commerce platforms. The results in this paper are thus of interest to crowdfunding practitioners, policymakers, and academics alike.

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Data Availability Statement

The (proprietary) data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1]Reward-based CFPs typically run more simultaneous campaigns than equity-based CFPs; hence, they provide a superior setting to identify spillover effects. The reasons are that reward-based crowdfunding projects are simpler to set up, and the screening process is lighter.

[2]Bikhchandani et al. (1998, p. 153) define social learning as an "influence resulting from rational processing of information gained by observing others."

[3]These estimates are based on Ulule data. However, our replication tests with KKBB data yield very similar economic effects.

[4]Kim, Newberry, and Qiu (2022) analyze backer behaviors on Kickstarter and find that displaying funding status and backer numbers significantly impacts campaign success. Unlike Ulule, which displays individual backers' funding history, Kickstarter only shows backer numbers as an aggregate statistic on the campaign page.

[5]Beyond crowdfunding, Haviv, Huang, and Li (2020) find positive intertemporal spillovers in video game platforms and Liang, Shi, and Raghu (2019) show positive spillovers generated by editor recommendations in the mobile app market.

[6]Belleflamme, Lambert, and Schwienbacher (2014) develop a model in which backers are heterogeneous in the way they value the community-based experience of engaging in a campaign, finding that this heterogeneity is crucial in shaping the entrepreneurial choice of reward-based crowdfunding.

[7]For an overview of the French crowdfunding market, see the website of the French Crowdfunding Association at https://financeparticipative.org.

[8]Financial rewards are not allowed.

[9]As of October 2024, Kickstarter reports under its "Stats" tab that about 35% of its backers are recurrent.

[10]This maximum number comes from one of Ulule's 10 partners who regularly back projects and are thus considered as recurrent backers. During our sample period, we identified 10 partners on Ulule who made a total of 1,038 contributions. The second largest number of contributions came from a backer who contributed 383 times.

[11]Supporting Information S1: Figure OA1 presents the total number of contributions made to projects each day throughout the funding cycle, aggregating campaigns of various durations. U-shaped patterns are observable at regular intervals (20, 30, 45, 60, 75, and 90 days).

[12]Given the dense set of fixed effects used, we prefer to use OLS models. However, average marginal effects of Probit models produce similar results.

[13]In Supporting Information S1: Table AO2, we replicate the main specifications of Tables 4 and 5 using contributions made on the KKBB platform. The estimation results are qualitatively similar, providing additional support to our predictions.

[14]Alternatively, we could assume that backers can contribute varying amounts to several projects; we could also consider two different but overlapping sets of campaigns. This would inevitably complicate the analysis without adding—we believe—any valuable insight for our limited purpose.

[15]Regarding the CFP under review, external growth can result from exogenous or endogenous reasons. Exogenous reasons are, for instance, the increased popularity of crowdfunding across the board or pure luck. Endogenous reasons can be advertising efforts made by the CFP or network effects, either direct (caused by word-of-mouth from previous backers or some attention effect) or indirect (more backers on day $t-1$ drive more entrepreneurs to join on day t, which makes the platform more attractive for new backers). As we cannot identify these different sources with our data, we do not distinguish them in the theoretical framework.

[16]We can talk here of "rational herding" insofar as new backers rationally aggregate information and do not ignore their own information (as their preferences also guide their choice); see Astebro et al. (2024) for a deeper analysis of herding in crowdfunding.

[17]We make the following assumptions regarding the "herding functions" $h(\cdot)$ and $H(\cdot)$. First, they are both increasing in their argument: $h'(\cdot) > 0$ and $H'(\cdot)$. Second, recurrent backers exert a stronger influence than non-recurrent backers: $H(z) > h(z)$ for any $z > 0$. Note that on CFPs like Kickstarter, recurrent backers cannot be identified. In that case, we would have that $H(\cdot) = h(\cdot)$.

[18]To see this, suppose that $K = 2$. Then $y^r_{1,t} > y^r_{2,t} \Leftrightarrow (\pi_{11} - \pi_{12})y_{1,t-1} > (\pi_{22} - \pi_{21})y_{2,t-1}$. It $\pi_{ii} = \pi$ and $\pi_{ij} = \pi' < \pi$, then $y^r_{1,t} > y^r_{2,t} \Leftrightarrow y_{1,t-1} > y_{2,t-1}$. If $y_{1,t-1} = y_{2,t-1}$, then $y^r_{1,t} > y^r_{2,t} \Leftrightarrow \pi_{11} + \pi_{21} > \pi_{22} + \pi_{12}$.

[19]Regarding our set of time-fixed effects, we closely follow prior literature using a similar panel data setting than ours (e.g., Kuppuswamy and Bayus 2017). This set of time-fixed effects captures significant variation in the data. For robustness, we re-estimate specification 6 by including calendar-day fixed effects, and we show that this adjustment does not qualitatively alter our conclusions (see Table 7).

[20]Together, the time-fixed effects and control variables capture the variation (over time and across projects) of all the parameters that we implicitly assumed to be constant in our theoretical framework, namely the rates of external and internal growth (μ and ρ), the number of contemporaneous projects (K), the "transition probabilities" (π_{ij}), the "herding functions" ($h(\cdot)$ and $H(\cdot)$), and the degree of differentiation across projects (τ_{ij}).

[21]By default, Ulule ranks projects according to a "Popularity" index, which is based on the contributions collected on the previous day. Although backers can 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 past day's contributions can affect current contributions.

[22]As suggested by our theoretical framework, this effect outweighs the relatively larger probability that recurrent backers have to contribute successively to projects within the same categories rather than switch categories.

[23]Recalling that we have a log-log model, this implies that a 100% increase in $Y_{i,t-1}$ multiplies y_{it} by $e^{0.215*\ln(2)} \approx 1.1607$.

[24]That is, a 10% increase in $Y_{-i,t-1}$ multiplies y_{it} by $e^{0.016*\ln(2)} \approx 1.0112$, and a 10% increase in $Y_{-j,t-1}$ multiplies y_{it} by $e^{0.054*\ln(2)} \approx 1.0381$.

[25]To conserve space, all the tests in this section are relegated to the Online Appendix.

[26]It could also be argued that what is important for cross-project spillovers is whether contributions to other live-campaigns were made, not the exact timing of those contributions (i.e., if they were made recently). Although taking the rolling average over various windows mitigates this concern, we also define our variables capturing cross-project spillovers by using the cumulative number of contributions made on other ongoing projects. Our results (untabulated) are similar.

[27]We note, however, that differentiating between cross-project spillovers within categories and across categories by creating coherent categories does not change qualitatively the results presented in Supporting Information S1: Table OA6.

[28]Panel B of Supporting Information S1: Table OA6 reports summary statistics for the variables used.

[29] $\rho^u = 0.127$ and $\rho^k = 0.068$ over the sample period (untabulated statistics); the increasing dominance of Ulule in terms of contributions is discussed in Section 6 and clearly depicted in Figure 3.

[30] It can also be argued that an entrepreneur's immediate circle supports the campaign on its first day, only to withdraw their contributions shortly thereafter. On Ulule, backers wishing to retract their contributions must do so before the campaign reaches its target goal. This practice is relatively uncommon on Ulule. Furthermore, none of the contributions made by backers during a strong initial start are deemed invalid.

[31] Recent econometric literature on staggered difference-in-differences highlights potential issues with the fixed effect estimator we used here (De Chaisemartin and d'Haultfoeuille 2020). The main insight from this literature is that the estimated parameter is a weighted average of each treatment (i.e., each fast start here) where the weights may be negative. We note, however, that our setting does not match the situation studied in this literature. Our treatment only lasts 1 day and a project can be treated multiple times. In other words, we estimate the average effect of cross-project spillovers only for the day of the fast start. Furthermore, in (untabulated) results we estimate the treatment effect for each event, as proposed by Sun and Abraham (2021), and obtain similar conclusions.

[32] As discussed in the Introduction, the crowdfunding literature has largely studied the effects of learning on within-project dynamics. This literature has provided evidence about whether and why information diffuses between backers of a given project. Recurrent backers are also likely to convey relevant information to other backers within the same project. We thus also examine the extent to which recurrent backers account for within-project dynamics. However, we mainly focus on their role in explaining cross-project spillovers, which is our main result.

[33] Our results (untabulated) 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 10.

[34] Since we do not have any information to cleanly capture cross-side network effects, we leave the empirical assessment of the relative importance of both learning and network effects for funding dynamics and spillovers for future research. To our knowledge, only a few papers document the presence of cross-side network effects on CFPs (Thies, Wessel, and Benlian 2018; Cong et al. 2020). 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 side (advertisers) often exerts negative network effects on the other side (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.

[35] For instance, τ_{ij} is larger when i and j belong to different categories than when they belong to the same category; note that in this formulation, $\tau_{ij} = \tau_{ji}$.

[36] That is, a new backer's preference may end up being located at any point in the interval with equal probability.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Appendix A

Theoretical Framework Details

We model the choice of a new backer in an Hotelling fashion by locating projects i and j at the extreme points of the unit interval. After examining the two projects, a new backer learns their position x on the unit interval, which indicates their relative preference for the two projects. A new backer's utility is then defined as follows:

$$U_t(x) = \begin{cases} u - \tau_{ij}x + h(y_{i,t-1}) + H\left(y^r_{i,t}\right) & \text{if contributing to project } i, \\ u - \tau_{ij}(1-x) + h(y_{j,t-1}) + H\left(y^r_{j,t}\right) & \text{if contributing to project } j, \end{cases} \tag{A1}$$

where u is the base utility from any project, τ_{ij} is a measure of the degree of differentiation between projects i and j,[35] $h(\cdot)$ measures the influence that the number of contributions to a given project in period $t-1$ has on the current decision to contribute to this project, and $H(\cdot)$ measures the same but for contributions of recurrent backers in period t. We make the following assumptions regarding the "herding functions" $h(\cdot)$ and $H(\cdot)$. First, they are both increasing in their argument: $h'(\cdot) > 0$ and $H'(\cdot)$. Second, recurrent backers exert a stronger influence than non-recurrent backers: $H(z) > h(z)$ for any $z > 0$.

From expression (A1), we can derive the identity, x_{ij}, of the new backer who would be indifferent between contributing to project i or j:

$$u - \tau_{ij}x_{ij} + h(y_{i,t-1}) + H\left(y^r_{i,t}\right) = u - \tau_{ij}(1-x_{ij}) + h(y_{j,t-1}) + H\left(y^r_{j,t}\right)$$

$$\Leftrightarrow x_{ij} = \frac{1}{2} + \frac{h(y_{i,t-1}) + H\left(y^r_{i,t}\right) - h(y_{j,t-1}) - H\left(y^r_{j,t}\right)}{2\tau_{ij}}.$$

If we assume that preferences are uniformly distributed on the unit interval,[36] then the probability that a new backer facing projects i and j will contribute to project i (resp. j) is equal to x_{ij} (resp. $1 - x_{ij}$). We can then compute the total number of contributions coming from new backers for any project. As there are K projects on the CFP, there are $\kappa \equiv K(K-1)/2$ different pairs of projects to which any new backer can be randomly exposed. Hence, each pair of projects is considered by Y_t/κ new backers. As each project is compared to each of the other $K-1$ projects by $Y_t/\kappa = (1+\mu)Y_{t-1}/\kappa$ new backers, we can express the number of new backers contributing to project i in period t, $y^n_{i,t}$, as:

$$y^n_{i,t} = \frac{1+\mu}{\kappa} Y_{t-1} X_{i,t} \quad \text{where } X_{i,t} \equiv \sum_{k \neq i} \left(\frac{1}{2} + \frac{h(y_{i,t-1}) + H\left(y^r_{i,t}\right) - h(y_{k,t-1}) - H\left(y^r_{k,t}\right)}{2\tau_{ik}} \right).$$

This is expression (3) presented in Section 4. We see that past contributions affect current contributions by new backers to some project in two multiplicative ways: a rise in previous contributions draws more new backers to the platform (effect of Y_{t-1}), while herding leads new backers to contribute more to projects that received relatively more contributions in the past (effect of $X_{i,t}$). In mathematical form, we have:

$$\frac{\partial y^n_{i,t}}{\partial y_{k,t-1}} = \frac{1+\mu}{\kappa} \left[X_{i,t} + Y_{t-1} \frac{\partial X_{i,t}}{\partial y_{k,t-1}} \right] \quad \text{for} i, k = 1 \ldots K.$$

To help us develop the latter expression, we introduce some additional notation. Let T_i denote the harmonic mean of τ_{ik} for $k \neq i$: $T_{-i} \equiv (K-1)/\left(\sum_{k \neq i} \frac{1}{\tau_{ik}}\right)$. We can then compute the following derivatives (with $z \neq i$ and recalling that $y^r_{i,t} = \rho \sum_{k=1}^{K} \pi_{ki}\, y_{k,t-1}$):

$$\frac{\partial X_{i,t}}{\partial y_{i,t-1}} = \frac{\kappa}{KT_{-i}} h'(y_{i,t-1}) + \frac{\rho}{2} \sum_{k \neq i} \frac{1}{\tau_{ik}} \left[\pi_{ii} H'\left(y^r_{i,t}\right) - \pi_{ik} H'\left(y^r_{k,t}\right) \right],$$
$$\frac{\partial X_{i,t}}{\partial y_{z,t-1}} = -\frac{1}{2\tau_{iz}} h'(y_{z,t-1}) + \frac{\rho}{2} \sum_{k \neq i} \frac{1}{\tau_{ik}} \left[\pi_{iz} H'\left(y^r_{i,t}\right) - \pi_{kz} H'\left(y^r_{k,t}\right) \right].$$

Combining the previous equations and recalling that $X_{i,t} = \kappa y^n_{i,t}/Y_t$, we can express the sensitivity of new backers' contributions to project i to changes in past contributions to project i or some other project $z \neq i$ as:

$$\frac{\partial y^n_{i,t}}{\partial y_{i,t-1}} = (1+\mu) \left[\frac{y^n_{i,t}}{Y_t} + \frac{Y_{t-1} h'(y_{i,t-1})}{KT_{-i}} + \frac{\rho Y_{t-1}}{K(K-1)} \sum_{k \neq i} \frac{\pi_{ii} H'\left(y^r_{i,t}\right) - \pi_{ik} H'\left(y^r_{k,t}\right)}{\tau_{ik}} \right],$$
$$\frac{\partial y^n_{i,t}}{\partial y_{z,t-1}} = (1+\mu) \left[\frac{y^n_{i,t}}{Y_t} - \frac{Y_{t-1} h'(y_{z,t-1})}{K(K-1)\tau_{iz}} + \frac{\rho Y_{t-1}}{K(K-1)} \sum_{k \neq i} \frac{\pi_{iz} H'\left(y^r_{i,t}\right) - \pi_{kz} H'\left(y^r_{k,t}\right)}{\tau_{ik}} \right].$$