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Research paper

In or out? Crowding effects in public goods with private gifts: Evidence from crowdfunding

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ABSTRACT

How do cumulative contributions influence subsequent giving to public goods that offer private gifts? While prior research has examined contribution dynamics in fundraising, the role of excludability — the property of preventing noncontributors from accessing the good — remains largely unexplored. We use comprehensive data from a reward-based crowdfunding platform to show that the excludability of a project significantly shapes its contribution pattern. We introduce two novel measures of excludability: one based on a good's inherent characteristics and another derived from the geographic distribution of backer-project distances. Our analysis reveals that more excludable goods (such as local projects and tangible products) exhibit stronger crowding-in effects, whereas less excludable ones (such as global projects and journalism) experience crowding-out effects. Although crowdfunding platforms systematically highlight cumulative contributions, our findings suggest that fundraisers should emphasize this information, particularly for excludable goods, but not for the least excludable ones.

1. Introduction

In fundraising for public goods, understanding how individuals respond to others' contributions is of great interest to practitioners and policymakers. Economic theory identifies two opposing mechanisms: cumulative pledges reduce the marginal utility of additional contributions (Bergstrom et al., 1986), leading to lower donations ("crowding-out"), or they signal project quality (Vesterlund, 2003), encouraging more donations ("crowding-in").[1] While extensive empirical evidence has examined the influence of others' financing, findings are mixed and often sector-specific. We argue that this heterogeneity partly stems from differences in project excludability—the property of preventing noncontributors from accessing the good. However, the role of excludability in shaping donor behavior and funding outcomes remains largely unexplored.

Studying excludability's role in crowding-out poses two key challenges. First, researchers must know the variability of public goods' characteristics while maintaining a constant donation environment. Second, measuring excludability reliably is essential. This study leverages detailed data from Ulule, a significant reward-based crowdfunding (RBCF) platform in France, to address both challenges. In RBCF, "backers" contribute relatively small amounts to support various causes, including technological, social, or artistic. In return, they receive nonmonetary rewards or gifts. Project owners set specific financial goals and receive the collected funds only if they meet their targets before the campaign ends.[2]

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[1] While social information and conformity also influence contribution patterns (Bergstrom et al., 1986; Smith et al., 2015), these effects primarily reinforce the underlying dynamics of crowding-in and crowding-out.

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RBCF is an ideal natural laboratory for studying our question for at least three reasons. First, crowdfunding resembles voluntary contributions to public goods jointly produced with private rewards (Varian, 2013; Belleflamme et al., 2014; Agrawal et al., 2015; Boudreau et al., 2021). Unlike traditional retail, backers fund production costs before the good exists. They contribute financially toward a project's potential realization (the public good) in exchange for promised rewards (private benefits). Second, projects vary in their level of excludability: some function as pure public goods (e.g., charity), while others resemble excludable public goods (e.g., concerts) (Hudik and Chovanculiak, 2018). RCBF platforms typically classify projects accordingly (e.g., "charity and citizens", "music"). This inherent heterogeneity provides a unique opportunity to systematically analyze contribution dynamics across different types of goods while keeping the contribution environment constant. Lastly, others' contributions are observable and salient to backers.[3] The literature on the crowding-out hypothesis typically examines how donors respond to changes in governmental spending, assuming they are aware of such changes. However, evidence suggests that donors often misestimate public spending levels (Horne et al., 2005; De Wit et al., 2017).[4] In RBCF, donors are directly exposed to cumulative funding levels, enabling a more accurate interpretation of the estimated effect.

We propose two complementary proxies to operationalize excludability. First, we leverage Ulule's project categorization system. While projects are grouped under main categories, creators can refine their classification by selecting subtags that specify the project's nature. For example, whether it involves a local event, produces a book, or supports a humanitarian cause. We construct an excludability score at the category-level based on the proportion of subtags related to societal causes, local events, or tangible products—concepts inherently tied to excludability. Second, we analyze the geographic distribution of backers. Excludability also arises from spatial distance. By examining the maximum distance between project owners and backers — our "geographic scope" — we capture the practical barriers to free consumption.

Our study contributes to two main streams of literature: (i) the relationship between past and subsequent contributions in fundraising for public goods with private gifts and (ii) funding dynamics in crowdfunding settings. First, we add to the extensive literature on the crowding effects in charitable giving (Bergstrom et al., 1986; Andreoni and Payne, 2011; Reinstein, 2011; Werfel, 2018). While most empirical research on crowding-out focuses on the substitution between aggregate private donations and public grants — often finding small or statistically insignificant effects (see De Wit and Bekkers (2017) or Tinkelman and Neely (2018) for a review) — our findings reveal that crowding-out estimates vary significantly with project excludability. Specifically, we observe crowding-out for the least excludable projects, while projects producing excludable goods exhibit crowding-in.

Our paper is also rooted in the burgeoning literature on crowdfunding (for a review of this literature, see Bouncken et al. (2015)). In particular, this study contributes to the growing literature that uses crowdfunding as a promising framework for studying giving behaviors (see, for example, Burtch et al. (2013), Meer (2014) and Smith et al. (2015)). While contribution dynamics have attracted significant scholarly interest (Agrawal et al., 2015; Kuppuswamy and Bayus, 2018; Kim et al., 2020; Belleflamme et al., 2025), existing studies primarily focus on extensive margins (e.g., the daily number of backers) and tend to examine either aggregate-level trends or sector-specific contexts. We extend this literature by providing evidence that these dynamics vary significantly depending on the type of projects being funded. Beyond addressing our core research question, this study also develops novel measures of excludability that can be broadly applied to studying public goods and collective action problems in crowdfunding.

The rest of the study is organized as follows. Section 2 reviews prior research on crowding-out in charitable donations, the role of excludability, and contribution dynamics in crowdfunding. Section 3 outlines the economic framework of Ulule, details our operationalization of excludability, and presents our empirical strategy. Section 4 reports the findings, and Section 5 provides a discussion and conclusion.

2. Related literature

2.1. Heterogeneity in crowding-out estimates

The crowding-out hypothesis states that when individuals are motivated by pure altruism, their charitable contributions will decrease proportionally as other funding sources — such as government support or private donations — increase. In its most extreme formulation, this hypothesis suggests that donors systematically reduce their giving by one dollar for every additional dollar provided by alternative sources, resulting in perfect crowding-out. Empirical research on crowding-out exhibits substantial heterogeneity in estimated effects, as documented in De Wit and Bekkers (2017) meta-analysis. This variation can partly be attributed to the context in which donations occur (experimental versus nonexperimental studies[5]), the funding sources (Hughes et al., 2014), the level of overall funding (Borgonovi, 2006; Ottoni-Wilhelm et al., 2017), or the degree of uncertainty donors face. In the latter case, governmental funding can signal the quality of a charitable cause and even lead to crowding-in (Payne, 2001; Heutel, 2014).

[2] In crowdfunding, two funding schemes can be adopted: the "all-or-nothing" one, where creators only receive funding if the funding goal is achieved, and the "keep-it-all" one, where creators can collect the funds even if the funding goal is not reached. This study focuses on the "all-or-nothing" model, which is mainly used in RBCF.

[3] When backers visit a project on Ulule, for instance, they can see a list of all the previous contributions made online as shown in Fig. 1(a).

[4] None of the 50 nonexperimental studies in De Wit and Bekkers's (2017) meta-analysis explicitly state that others' contributions are salient to donors. Moreover, despite evidence that donors poorly estimate public funding, in 11 of these studies, authors use yearly lagged variables on governmental spending to evaluate crowding-out.

[5] In their meta-analysis, De Wit and Bekkers (2017) show that in experiments, a $1 increase in government support is associated with an average $0.64 decrease in private donations, while non-experimental data analyses find an average increase of 0.06.

Theoretically, crowding-out should not only appear between public and private donations but also between private donations and any other funding source. Several papers have directly tested the impact of other donors' contributions on subsequent donations and have generally supported the hypothesis of complementarity of donations. For instance, Martin and Randal (2008) conducted a natural field experiment in an art gallery by varying the monetary content of a donation box and found that donors react positively to others' contributions. Similarly, Shang and Croson (2009) showed that mentioning a high contribution made by another donor during an on-air fund drive for a local public radio station increases individual contributions. These studies underscore the importance of others' behavior as social information about the appropriate amount one should donate. However, they focused on relatively local initiatives and the impact of individual donations rather than cumulative ones.

Few papers compare crowding-out estimate across sectors. Tinkelman and Neely (2018) advocate for targeted research within specific contribution domains to uncover distinct donor motivations and funding dynamics, arguing that aggregated analyses across multiple sectors can obscure critical differences. While there is broad evidence of variation in contribution dynamics across sectors (Brooks, 2000; Andreoni and Payne, 2011; Grasse et al., 2022), little is known about the underlying factors driving these differences. For example, some studies on performing arts find crowding-in, where private donations increase alongside public funding (Smith, 2003, 2007). In contrast, research on public radio suggests crowding-out (Kingma, 1989; Brooks, 2003). We argue that this difference can be attributed to the inherent excludability of these goods: performing arts offer direct, exclusive benefits to donors, whereas public radio broadcasts remain accessible to all listeners regardless of their contributions.

2.2. Excludability, crowding-in, and crowding-out

A public good is defined by two fundamental properties: nonexcludability, meaning individuals cannot be prevented from using it without incurring substantial costs, and nonrivalry, where one person's consumption does not diminish its availability to others. However, in practice, few goods perfectly exhibit both properties.[6] Young et al. (2019) argue that many goods traditionally labeled as "public goods" are more accurately described as "collective goods"—resources that remain nonrivalry but can be made excludable to varying degrees.

Excludable collective goods, such as live artistic performances, allow only paying donors to access private benefits. In the context of RBCF, only backers are rewarded with access to excludable goods, while both backers and nonbackers could benefit from nonexcludable ones. Varian (2013) explores how combining public goods with private gifts creates a mechanism akin to Andreoni's "warm glow" model, in which impure altruism leads to incomplete crowding-out. In a model where others' contributions signal public good quality, the presence of private gifts might even reinforce crowding-in effects, as the signaling mechanism operates on both altruistic and self-interested motivations simultaneously. Kotchen and Wagner (2023) find support for this prediction in volunteering: crowding-in is stronger for environmental parks than nonenvironmental parks because volunteers can enjoy the exclusive recreational benefits from the former.[7]

Excludability and private benefits influence not only contribution levels but also the composition of the donor pool. When goods are nonexcludable, individuals are incentivized to free-ride on others' contributions, leaving contributions primarily to altruistically motivated individuals. Goette and Stutzer (2020) demonstrate through a blood donation field experiment that offering private rewards (such as lottery tickets) disproportionately attracts less intrinsically motivated donors. This selection effect has significant implications for contribution patterns. At the extreme, nonexcludable goods attract altruists who may crowd out on others contributions, while excludable goods attract donors drawn by private gifts and who never crowd out.

2.3. Contribution dynamics in crowdfunding

While early research on crowdfunding has primarily focused on the determinants of successful campaigns (Mollick, 2014), scholars have increasingly examined how prior funding influences subsequent contributions. Studies on RBCF generally report a positive relationship between past and future contributions (Agrawal et al., 2015; Kuppuswamy and Bayus, 2017; Kim et al., 2020; Belleflamme et al., 2025). This pattern aligns with the hypothesis of herding behavior, where donors interpret past contributions as a quality signal to navigate the high uncertainty of early-stage RBCF projects (Zhang and Liu, 2012). However, three notable exceptions suggest that crowding-out may occur: in publishing crowdfunding (Burtch et al., 2013), in crowdfunding for technological products when prior funding amounts are low (Chan et al., 2020), and in civic crowdfunding (Brent et al., 2019). Notably, Brent et al. (2019) found crowding-out when restricting their sample to donations from distant backers. These findings suggest that whether backers directly benefit from a project's realization may influence contribution dynamics.

Most RBCF studies analyze contribution patterns using the extensive margin (i.e., the number of new backers per day) (Agrawal et al., 2014; Kuppuswamy and Bayus, 2018; Belleflamme et al., 2025), while fewer focus on the intensive margin (i.e., contributed amounts) (Smith et al., 2015; Bernard and Gazel, 2017; Brent et al., 2019). This emphasis on the extensive margin overlooks key qualitative differences: Higher funding levels may attract more donors (indicating crowding-in) while reducing the average contribution size of pure altruists (indicating crowding-out). This study focuses on the intensive margin as it provides a more direct

[6] While national defense and public lighting are often cited as canonical public goods, even these examples may involve private benefits. As Varian (2013) notes, in Coase's (1974) famous lighthouse example, ships paid lighthouse fees when docking at ports. One could view the total payment as a contribution to the provision of the public lighthouse, with the dock usage as a private benefit. National defense could also be seen as less effective, at least in the short term, as the proximity to a concentration of military forces decreases.

[7] For instance, environmental parks may provide volunteers with additional hiking trails and boardwalks while volunteering.

test of crowding-out: While the extensive margin captures whether individuals decide to contribute, the intensive margin reveals how they adjust their contribution levels in response to others' giving.

The remainder of the study empirically examines how cumulative contributions influence subsequent donations on Ulule. Based on the literature review, both crowding-out and crowding-in effects are possible. However, we expect these effects to vary depending on the level of excludability of the projects. First, cumulative contributions may serve as a quality signal, a mechanism that might be reinforced in the presence of a private reward. Second, private rewards for excludable goods may attract self-interested donors, altering the donor pool. Thus, we anticipate stronger crowding-in effects for highly excludable projects and stronger crowding-out effects for less excludable ones.

3. Data and empirical strategy

3.1. The data

We use contribution-level project data from the crowdfunding platform Ulule (www.ulule.com) to estimate crowding effects. Founded in 2010, Ulule has grown into a leading crowdfunding platform in France, boasting over 6 million members and successfully funding over 49,000 projects, with a success rate of 67% in 2025. The platform supports various project categories, including film, music, arts, and charity.[8] Before launching a campaign, project owners must undergo a validity check, during which they receive assistance in selecting the appropriate category and creating a compelling pitch. Project owners can also use keyword hashtags as subtags to specify their project's nature better. Ulule operates on an "all-or-nothing" funding model, meaning creators receive funds only if they reach their funding goal. Backers can contribute with or without receiving rewards, including preorders of the final product, special editions, or tokens of appreciation such as thank-you notes. Once the goal is met, the project owner is responsible for fulfilling the promised rewards. Cumulative contributions are displayed on each project's page, allowing backers to track its progress (see Fig. 1(a)). The same also displays a list of subtags alongside the project's main category, as shown in Fig. 1(b). Notably, most of Ulule's backers are unique users, with 85% of our raw sample having supported only one project.

Our dataset includes all available information from Ulule regarding project owners and backers. It allows us to track the projects, as well as the timing and amounts of all contributions made by backers registered on the platform. Initially, the dataset provided by Ulule consisted of 1,287,656 contributions to 23,518 European projects launched on the Ulule platform from July 15, 2010, to April 14, 2016. We retain projects validated by Ulule for public display and exclude those canceled or considered fraudulent by the platform. For comparability, we focus on projects whose owners are based in France, as France represents Ulule's largest market, and exclude projects with durations in the bottom 5th percentile or top 95th percentile of the distribution. We exclude projects classified as "other projects" or without classification. To ensure data validity, we remove instances of auto-financing — contributions made by project owners to their projects — as well as special contributions made by Ulule or its partner companies. Our final sample comprises 926,515 contributions to 16,498 projects from 693,236 backers. Summary statistics for our working sample, including the variables used in our empirical analysis, are presented in Table A.2 in Appendix.

3.2. Empirical strategy

To proxy the level of excludability, we use two types of variations: the project's category and geographic scope. These proxies offer complementary advantages. The project category is an exogenous variation, as creators are unlikely to shift from one category (e.g., producing an album) to another (e.g., developing a video game) in the short run. However, platform-defined categorizations may introduce some heterogeneity within categories. For example, the music category includes concert organization and album production. In contrast, the geographic proxy enables more standardized comparisons but may be subject to endogeneity, as creators may strategically choose to produce local or global goods. This section introduces the two proxies and the corresponding empirical strategies.

3.2.1. Project category

In our empirical specification, we leverage differences in project categories (denoted as main category k) to examine the relationship between crowding-out and excludability. Our analysis includes all main categories as defined by Ulule: childhood and education, comics, charity and citizens, film and video, publishing and journalism, music, crafts and food, stage, technology, heritage, games, sports, arts and photos, and fashion and design.[9] To investigate crowding-out, we estimate the following specification:

$$\begin{aligned}\log(c_{ijt}) = \quad & \alpha_0 + \sum_k \beta_{1k} \mathbb{1}[CAT_k]_j + \sum_k \beta_{2k} log(C_{jt}) \times \mathbb{1}[CAT_k]_j \\ & + \gamma W_j + \delta X_i + \eta M_{ijy} + FE_t + \varepsilon_{ijt},\end{aligned} \tag{1}$$

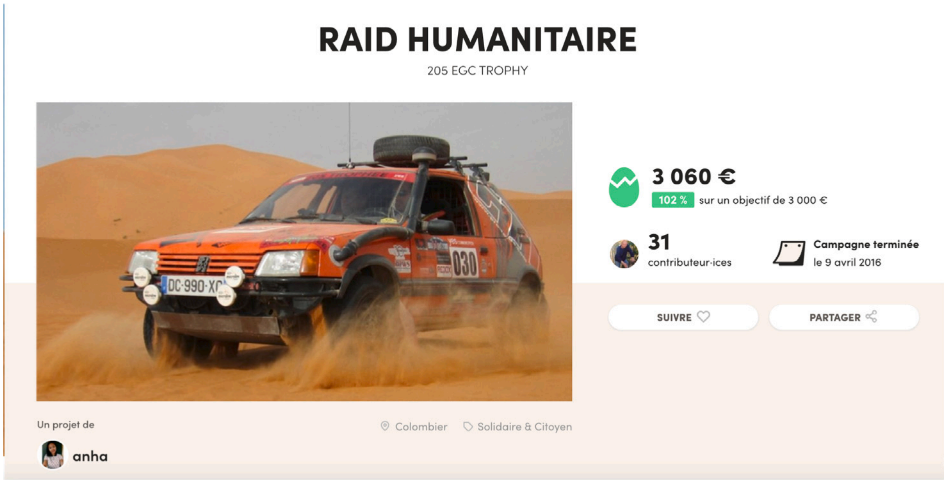
where c_{ijt} is the contribution of individual i to project j at time t, and C_{jt} is the cumulative contribution of a project in euros. Due to the left-skewed nature of this variable, we apply a logarithmic form, which also allows us to interpret coefficients as semi-elasticities.[10] FE_t represents time-fixed effects and includes year, month, and weekday fixed effects. We control for a set of project

[8] See Table A.1 for a brief description of the main categories on Ulule.

[9] Descriptive statistics by main categories are provided in Table A.3 in Appendix.

[10] To address extreme values, contributions are winsorized at the 99th percentile.

(A) Example of a webpage on Ulule



(B) Example of subtags

Fig. 1. Screenshots of Ulule project Raid Humanitaire.
Notes: The figure displays screenshots of the Ulule project, Raid Humanitaire. The total cumulative contributions (€3060) are prominently displayed in the top right corner of the page, as indicated in Panel (A). At the bottom of the page, the project's main category ("charity and citizens") and subtags ("weird" and "humanitarian") are presented, as shown in Panel (B).

characteristics W_j, including the funding goal (in log), campaign duration, project owner type (individual, business, or association), number of news updates published by the project owner, number of project subtags, presence of limited-stock rewards, and the average income of the project's region. Additionally, we control for backer-level characteristics (X_i), such as the backer's age at time t and their total number of supported projects. Contribution-level controls (M_{ijy}) account for whether the backer contributed without selecting a reward, joined the platform on the same day the contribution to project j was made, made a cash payment, or made the contribution that helped the project reach its funding goal. Standard errors are clustered at the project level.[11]

To estimate heterogeneous crowding effects, we introduce indicator variables $\mathbb{1}[CAT_k]_j$, which take a value of 1 when project j belongs to category k (as defined by Ulule). The coefficients of primary interest are β_{2k}, which estimates the crowding effects for each category k. A negative coefficient indicates crowding-out, while a positive coefficient indicates crowding-in. We expect stronger crowding-in effects for categories with higher excludability.

Which categories are more excludable? The interpretability of our estimates is challenged by the heterogeneity within each category. For example, the music category may include projects to produce an album, support a charitable cause, or organize a local concert.[12] To address this issue, we leverage the subtags assigned by project owners to refine our understanding of each main category. Approximately 80% of the projects in our working sample feature subtags.[13] We use these subtags to identify the nature of each project systematically.

We define three subcategories related to excludability: "societal cause", "local event", and "tangible product". The "societal cause" subcategory includes projects about standard public goods, characterized by subtags such as *solidarity*, *humanitarian*, or *green*. The other two subcategories, "local event" and "tangible product", will likely exhibit more excludability. "Local event" is identified

[11] All our findings remain robust when we cluster the standard errors at the backer level rather than at the project level.
[12] The projects Dei, Musique en Ville, and Sos Enfants are examples of the three respective cases.
[13] The list and summary statistics of subtags are provided in Table A.4.

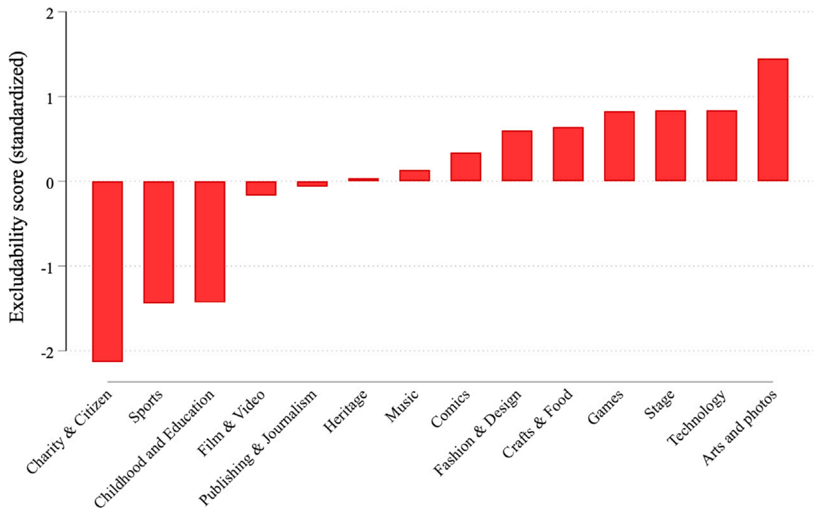


Fig. 2. Excludability score (standardized) by categories.
Notes: To define the excludability score for each main category k, we sum the proportions of projects falling under three subcategories: "societal cause" (assigned a negative value), "local event", and "tangible product". The excludability score is then standardized.

using the subtags *stage* and *places*, while "tangible product" includes those tagged with *DIY*,[14] *craftsmanship*, *technology*, *photography*, *fine arts*, or *boardgame*.[15]

To define the excludability score for each main category k, which consists of n_k projects in our sample, we sum the proportions of projects that fall into three subcategories: "societal cause" (assigned a negative value), "local event", and "tangible product".[16] The excludability score for category k is given by:

$$\text{Excludability}_k = \frac{1}{n_k}[\sum_{j=1}^{n_k} \mathbb{1}[\text{Local event}]_j + \sum_{j=1}^{n_k} \mathbb{1}[\text{Tangible product}]_j - \sum_{j=1}^{n_k} \mathbb{1}[\text{Societal Cause}]_j]$$

Dummies $\mathbb{1}[\text{Local event}]_j$, $\mathbb{1}[\text{Tangible product}]_j$, and $\mathbb{1}[\text{Societal Cause}]_j$ are set to 1 when project j falls into the respective subcategories. Based on this excludability score, the main categories — sports, charity and citizens, and childhood and education — are identified as the least, while craft and food, technology, and arts and photos are the most excludable, as shown in Fig. 2. We then standardize the final score and expect β_{2k} to correlate with the excludability score positively.

3.2.2. Project geographic scope

A second way to proxy a project's excludability level is through its geographic scope—specifically, the extent to which a project benefits a global versus a local area. Impure public goods may arise due to the possibility of exclusion based on space or distance (Blackwell and McKee, 2003)—accordingly, the greater a project's geographic scope, the lower its level of excludability.

We propose a measure of geographic scope based on actual incentivized contribution choices, leveraging data on the distribution of backer-project distance.[17] A project's geographic scope is the maximum distance between a backer and the owner. On average, this measure is 1165.28 km (sd = 2200.40). To further analyze variation, we divide the sample into quartiles based on the distribution of geographic scope at the project level, labeling them from "very local" (Q1) to "very global" (Q4) (see Table 1 for the descriptive statistics).

Our estimation strategy is similar to Eq. (1); however, instead of using Ulule categories k, we employ indicator variables $\mathbb{1}[SCOPE_s]$, which take a value of 1 when project j falls within geographic scope s (ranging from very local, $s = 1$, to very global, $s = 4$). Our estimation specification is as follows:

$$\begin{aligned} \log(c_{ijt}) = \quad & \alpha_0 + \sum_s \beta_{1s}\mathbb{1}[SCOPE_s]_j + \sum_s \beta_{2s} log(C_{jt}) \times \mathbb{1}[SCOPE_s]_j \\ & + \gamma W_j + \delta X_i + \eta M_{ijy} + FE_t + \varepsilon_{ijt} \end{aligned} \tag{2}$$

[14] DIY stands for "do it yourself". It refers to making or repairing things oneself instead of hiring a professional or buying a premade product. DIY can involve many activities, from home improvement projects to crafting and artistic endeavors. For example, one project from the main category "charity and citizens" used the subtag *DIY* as the project to organize workshops to create potteries to facilitate local integration.

[15] We have excluded subtags that refer to potential digital products like music, book, or comics since they are easily accessible if digitized.

[16] The proportions by main categories for each subtag are provided in Table A.4 in Appendix.

[17] This information is available for 13,941 projects of our sample.

Table 1
Descriptive statistics by geographic scope.

	Very local	Local	Global	Very global
Geographic scope	184.04	512.65	659.05	3306.45
	(142.27)	(59.73)	(31.28)	(3622.30)
Goal	2286.64	2718.03	3279.54	4420.96
	(2693.38)	(3094.45)	(3897.23)	(7391.31)
Duration (in days)	39.98	40.74	41.29	42.04
	(12.32)	(12.18)	(12.23)	(12.11)
Amount collected (in euros)	954.04	2104.49	3086.92	5894.39
	(1256.48)	(2191.60)	(3456.43)	(19254.35)
# of contribution	18.70	38.86	56.59	111.68
	(17.77)	(32.05)	(52.77)	(323.59)
Successful campaign	0.47	0.75	0.83	0.87
	(0.50)	(0.44)	(0.37)	(0.34)
Obs.	3486	3486	3485	3484

Notes: The geographic scope of a project is defined as the maximum of the backer-creator distance distribution within our working dataset. Projects are then divided into four quartiles based on this distribution. We categorize the quartiles according to their geographic scope, ranging from very local (Q1) to very global (Q4). Standard errors are in parentheses.

In this case, β_{2s} estimates crowding-out for each geographic scope s. Since global projects are expected to be less excludable, we anticipate $\beta_{24} < \beta_{23} < \beta_{22} < \beta_{21}$.

4. Results

4.1. Crowding-in, crowding-out, and project category

We first estimate Eq. (1) to compare crowding-in and crowding-out effects across the main project categories.

Fig. 3 presents the estimated marginal crowding-in or crowding-out (β_{2k}) for each main category. Our findings indicate significant variation in crowding effects across categories. Specifically, a 1% increase in cumulative contributions is associated with subsequent contribution changes ranging from a decrease of 0.028% in the "publishing and journalism" category to an increase of 0.073% in the "games" category. Fig. 4 illustrates the estimated average marginal effects and excludability scores of the main categories k, highlighting the relationship between excludability and crowding effects. A nonparametric Spearman test reveals a significant positive correlation between our estimated crowding effects and the excludability score ($r_s = 0.521$, $p = 0.057$).

Several key insights emerge from our findings. First, "publishing and journalism" is the only category exhibiting crowding-out, consistent with prior empirical research on digital journalism (Burtch et al., 2013). This effect is mainly driven by journalism projects, as shown in column (1) of Table A.6 in the Appendix, which closely aligns with the characteristics of a pure public good. Conversely, crowding-in is observed across multiple categories: "music", "technology", "heritage", "fashion and design", "arts and photos", and "games". Most of these categories produce tangible products.

The "music" category presents a nuanced case. As previously discussed, it includes projects to produce an album or organize a local event. Further estimations, restricting the sample to music projects, reveal that crowding-in effects are driven by projects focused on concert production (see column (2) of Table A.6 in the Appendix). The "games" category requires cautious interpretation. Project owners in this domain often employ a unique "campaign gamification" strategy, dynamically adjusting financial objectives and reward structures based on intermediate milestones.[18] This multi-thresholds approach incentivizes backers by offering progressively unlockable rewards and stretch goals, potentially driving the observed crowding-in.

To further examine the role of excludability across project categories, we extend our analysis by estimating Eq. (1) with interaction terms between $LogC_{jt}$ and dummy variables for "societal cause", "local event", and "tangible product" while controlling for main category fixed effects. These estimations are conducted across the entire sample and various project subsamples, with findings detailed in Table 2. The interaction term Societal Cause $\times$ $LogC_{jt}$ is not statistically significant at conventional levels, except when the sample is restricted to creative projects (comics, film and video, games, music, and publishing and journalism) or tangible projects (art and photo, craft and food, fashion and design, and technology). Notably, we consistently observe a positive and statistically significant interaction coefficient for projects that involve organizing local events or producing tangible goods that are inherently more excludable.

The coefficient β_{1k} captures the average amount contributed for category k at the beginning of the fundraising campaign. As shown in Table A.5 in the Appendix, our findings suggest that β_{1k} is greater for less excludable categories, such as "publishing and journalism", "charities and citizens", and "film and videos". One possible explanation is that initial contributions are larger for less excludable projects because altruistic backers donate more in the absence of C_{jt}, which would otherwise crowd-out their

[18] For example, the Appel de Cthulhu project employed this technique.

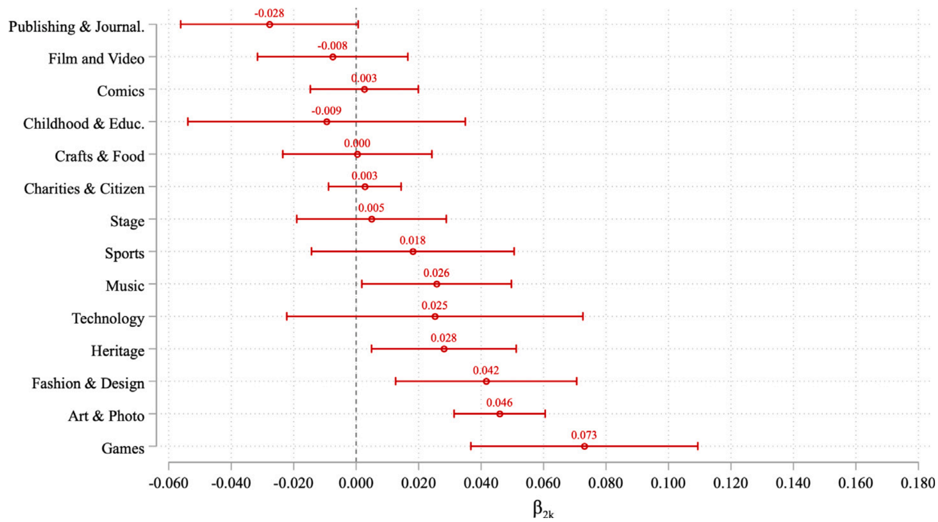


Fig. 3. Average marginal effects β_{2k} by main category k.
Notes: Each point represents the average marginal effect of $Log(C_{jt})$ for category k (β_{2k}) and its 95% CI using Eq. (1). The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. The specification includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors are clustered at the project level. The estimated model is presented in Table A.5 in Appendix.

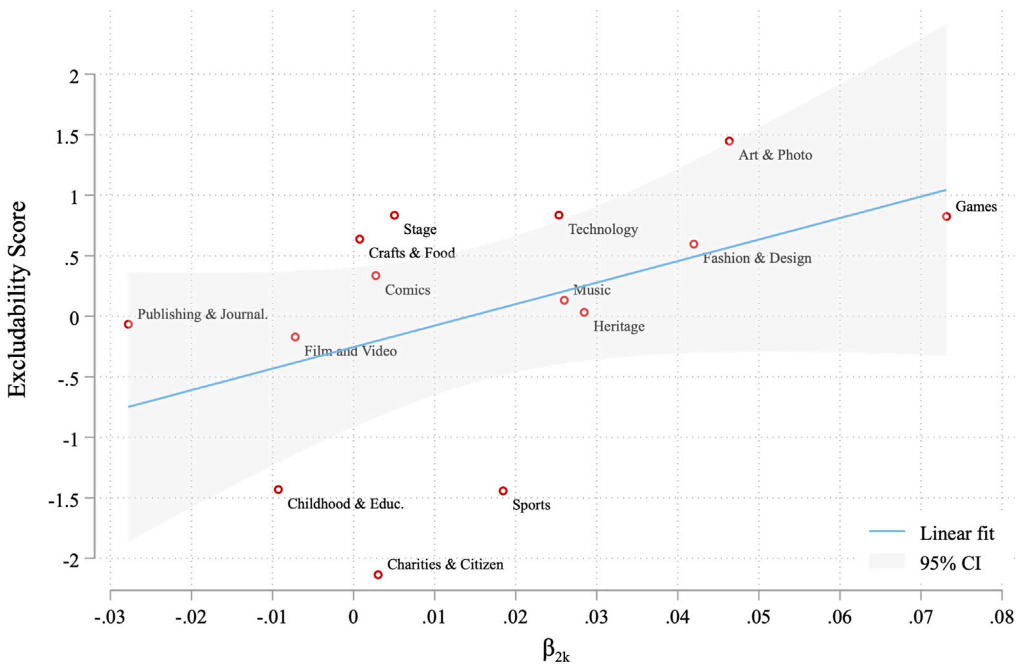


Fig. 4. Scatter plot of average marginal effect β_{2k} by main category and excludability score.
Notes: Each point on the scatter plot represents the coefficients β_{2k}, the average marginal effect of $Log(C_{jt})$ for category k, with the category's excludability score on the y-axis. A nonparametric Spearman test reveals a positive and significant correlation between the two variables ($r_s = 0.521$, $p = 0.057$).

Table 2
Crowding out effects, by subcategories (OLS).

	All projects				Societal projects				Creative projects				Tangible projects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	$Logc_{ijt}$				$Logc_{ijt}$				$Logc_{ijt}$				$Logc_{ijt}$			
$LogC_{jt}$	0.009***	0.015***	−0.005	−0.008	0.021***	0.006	0.019***	0.000	0.000	0.004	−0.017***	−0.013**	0.016***	0.029***	−0.007	0.016
	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.015)	(0.004)	(0.015)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.012)	(0.014)
Local event × $LogC_{jt}$	0.019***			0.028***	0.028**			0.033**	0.012			0.017*	0.028			0.020
	(0.006)			(0.007)	(0.012)			(0.013)	(0.009)			(0.009)	(0.024)			(0.023)
Societal cause × $LogC_{jt}$		−0.013*		0.001		0.020		0.022		−0.033***		−0.024**		−0.039**		−0.035**
		(0.007)		(0.007)		(0.017)		(0.017)		(0.012)		(0.012)		(0.016)		(0.016)
Tangible product × $LogC_{jt}$			0.041***	0.042***			0.030***	0.033***			0.040***	0.036***			0.032**	0.014
			(0.007)	(0.008)			(0.010)	(0.011)			(0.011)	(0.010)			(0.016)	(0.016)
Observations	535 012	535 012	535 012	535 012	145 373	145 373	145 373	145 373	265 945	265 945	265 945	265 945	81 327	81 327	81 327	81 327
Clusters	10 695	10 695	10 695	10 695	3710	3710	3710	3710	4254	4254	4254	4254	1735	1735	1735	1735

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents estimates from ordinary least squares regressions specified using the interaction between $LogC_{jt}$ and dummy variables at the project level for "local event", "societal cause", and "tangible product." Columns (1)–(4) present findings for the full sample. Columns (5)–(8) present findings for the societal projects only (charity and citizen, childhood and education, and sports). Columns (9)–(12) present results for the creative projects only (comics, film and video, games, music, and publishing and journalism). Columns (13)–(16) present findings for the tangible projects only (art and photo, craft and food, fashion and design, and technology). All specifications include time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors (in parentheses) are clustered at the project level.

contributions. However, this interpretation should be approached with caution: variations in initial contributions across categories may also reflect differences in the underlying valuations of goods rather than solely the effect of excludability.

Our broader findings indicate that crowding-in predominantly characterizes the crowdfunding landscape, with the magnitude of this effect critically dependent on a project's excludability.

Robustness checks. We conduct additional robustness tests to validate our findings. The findings remain consistent when we restrict the sample to contributions made before projects reached their funding goal and when considering unique backers (see Fig. A.1 in the Appendix). Notably, crowding-out for the "publishing and journalism" category becomes more pronounced when restricting the sample to contributions made before the goal is met. This suggests that altruistic backers — who drive crowding-out — are more likely to contribute when their funds are most needed. The scarcity of rewards may influence the range of contribution values and increase excludability. Our findings also hold when excluding projects with depleted limited rewards, defined as those where at least one reward with a limited quantity was fully claimed before the campaign ended.[19] The average marginal effects by main categories, presented in Fig. A.2 in the Appendix, yield similar findings. Finally, we replicated the estimation by interacting cumulative contributions with our continuous excludability score (standardized), replacing dummy variables for each category. This approach produced a significant positive coefficient for the interaction term Excludability Score × $LogC_{jt}$ ($\beta_2 = 0.011$, SE = 0.003, $p < 0.001$), further supporting our core hypothesis.

4.2. Crowding-in, crowding-out, and geographic scope

We now estimate Eq. (2) to compare the estimated β_{2s} across the project's geographic scope.

Fig. 5 presents the estimated average marginal crowding effects (β_{2s}) across different geographic scopes. We find the strongest crowding-in effects for very local projects, where a 1% increase in cumulative contributions leads to a 0.058% increase in subsequent donations. This effect decreases monotonically as projects become more geographically dispersed, with local and global showing progressively smaller crowding-in coefficients. Notably, very global projects exhibit crowding-out effects ($\beta_{24} = -0.008$), suggesting that increased funding may marginally discourage subsequent contributions for these widely dispersed projects.

Table A.7 in the Appendix confirms that β_{1s} is higher for more global projects. Consistent with our findings on β_{1k}, initial contributions are higher for less excludable projects, likely because altruistic backers provide greater support when funding is most needed. As campaigns progress and total contributions increase, the average donation amount decreases, suggesting altruistic backers either reduce their contributions or withdraw entirely from participation.

Our findings suggest that contribution dynamics exhibit crowding-out effects for very global, less excludable projects. Conversely, projects primarily attracting local backers generate private benefits for contributors, making them less susceptible to being crowded out by others' contributions. To further connect the results from our two proxies of excludability, Fig. 6 plots the estimated β_{2k} from Eq. (1) against the category-level share of contributions made to very global projects. The latter can be interpreted as an alternative measure of nonexcludability at the category level. As previously noted, the "games" category stands out as an outlier. Although about 80% of the contributions in this category go toward very global projects, they exhibit the strongest crowding-in effects. This result may stem from the multi-threshold strategies employed by project owners. For all other categories, we observe a negative correlation between the share of contributions to very global projects and the level of crowding-in, as expected.

[19] The 16,498 projects in our working sample collectively proposed 121,789 unique rewards. Among these rewards, 15% were categorized as limited supply, and 1.8% were depleted, meaning the stock limit was reached.

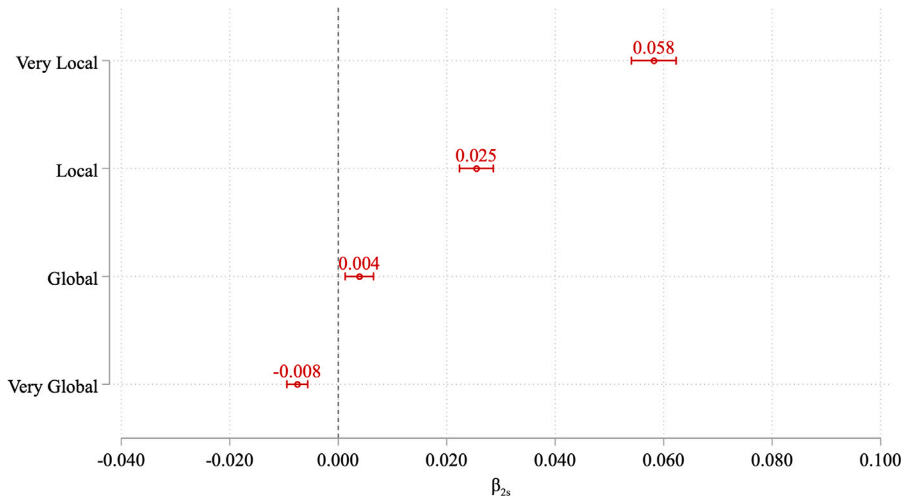


Fig. 5. Average marginal effects β_{2s} by geographic scope.
Notes: Each point represents the average marginal effect β_{2s} of $Log(C_{jt})$ by geographic scope s (ranging from very local to very global) with a 95% CI using Eq. (2). The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. The specification includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors are clustered at the project level. The estimated model is presented in Table A.7 in Appendix.

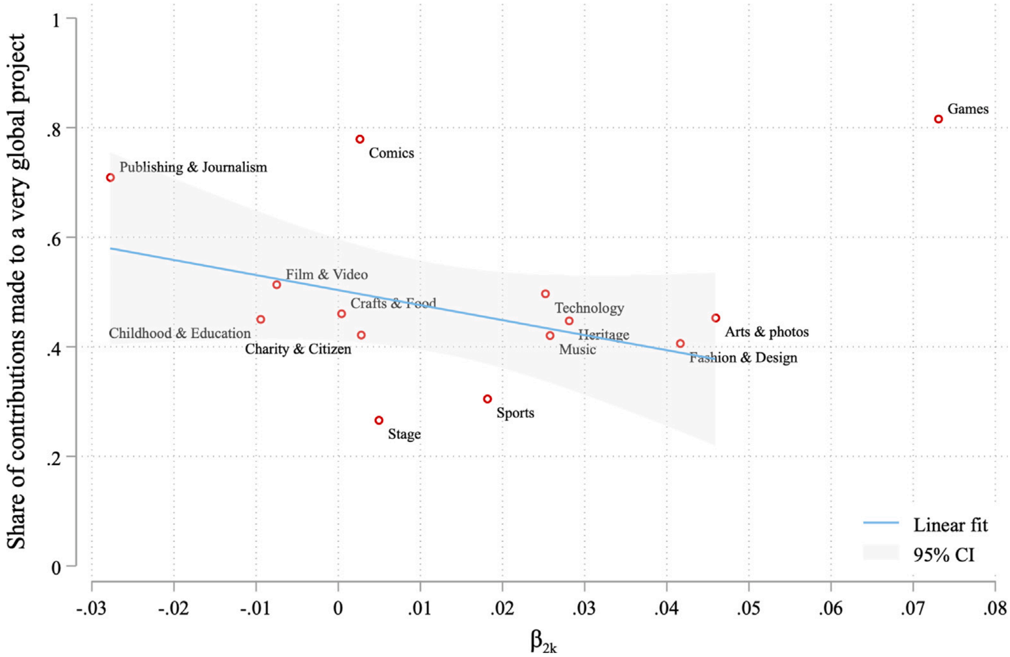


Fig. 6. Scatter plot of average marginal effect β_{2k} by main category and share of contributions made to very global projects.
Notes: Each point on the scatter plot represents the coefficients β_{2k}, the average marginal effect of $Log(C_{jt})$ for category k, with the share of contributions of a given category made to a very global project on the y-axis. A nonparametric Spearman test, excluding the "games" category, reveals a negative correlation between the two variables ($r_s = -0.484,\ p = 0.094$).

Robustness checks. We conduct several robustness checks to validate our main findings. The findings remain consistent when we estimate Eq. (2) restricting our sample to contributions made before projects reached their goal, when considering unique backers only, and when excluding projects with depleted rewards (see Figs. A.3 and A.4 in the Appendix). Interestingly, for very global projects only, crowding-out intensifies to −0.036 when considering only contributions made before reaching the funding objective. This pattern suggests that, for nonexcludable goods, altruistic donors that drive crowding-out effects are more likely to contribute when their funds are most needed. Our findings also remain robust when we interact the logarithm of cumulative funding with the maximum distance between backers and projects instead of using categorical variables for geographic scope. Furthermore, our findings hold under alternative specifications of geographic scope, including definitions based on the 98th or 99th percentile threshold (see Table A.8 in the Appendix).

5. Conclusion

Leveraging comprehensive data from Ulule, a leading French crowdfunding platform, this article systematically analyzes the effect of cumulative contributions on subsequent ones in public goods with private gifts. We show that, overall, backers increase their contribution as the cumulative funding increases (crowding-in). However, our findings suggest that both the direction and magnitude of crowding effects depend on a project's level of excludability—the property of preventing noncontributors from accessing the good. Our analysis reveals that more excludable goods exhibit stronger crowding-in, whereas less excludable ones experience crowding-out. Our findings remain robust when excluding over-the-objective contributions, restricting the sample to unique backers, or excluding projects with depleted rewards.

Our analysis reveals substantial variation in the influence of cumulative contributions across categories. A 1% increase in cumulative funding corresponds to a 0.028% decrease in contributions for "publishing and journalism" projects. For "fashion and design" or "arts and photo", this elasticity becomes positive (0.042% and 0.046%, respectively). In particular, projects featuring local events or tangible products exhibit crowding-in effects, while those focused on societal causes experience either crowding-out effects or no effect. We establish a relationship between excludability and crowding effects by building a category-level excludability score based on project subtags. Categories with higher excludability scores exhibit stronger crowding-in effects.

Our findings indicate that the geographic scope of a project — our second measure of excludability — affects contribution dynamics. Local projects tend to exhibit crowding-in behavior, with an elasticity of 0.058, whereas more global projects show signs of crowding-out, with an elasticity of -0.008. Crowding-out intensifies to -0.036% for very global projects when considering only contributions made before reaching the funding objective. This pattern suggests that for nonexcludable goods, altruistic donors that drive crowding-out effects are more likely to contribute when their funds are most needed—before the project reaches its goal.

These findings are relevant for practitioners seeking to leverage peer effects in crowdfunding. By understanding these cross-category insights, project owners and platforms can emphasize cumulative funding for local and excludable goods to maximize total contributions. Producing tangible products, and thus including tangible rewards for backers, might also foster crowding-in by attracting donors who respond positively to cumulative contributions. Our findings are also valuable for policymakers aiming to identify conditions under which private and public finance are likely to complement or substitute each other at the sector level.

The "games" category emerges as a notable outlier in our results. Despite being largely composed of projects with a broad geographic scope, it exhibits the strongest crowding-in effect. One possible explanation for this unexpected pattern is the frequent use of multi-threshold strategies by project owners—where reaching an initial funding goal unlocks a new, higher target. This approach may incentivize continued contributions, counteracting the typical crowding-out effects observed in very global projects. Exploring the implications of such strategies presents an interesting avenue for future research.

Finally, our findings provide novel insights into how excludability shapes crowdfunding contribution dynamics. While observational data ensures strong external validity, future research could complement these findings through experimental studies. A controlled experiment would allow for precise manipulation of excludability mechanisms, offering greater internal validity.

Data from crowdfunding platforms enable researchers to overcome many empirical limitations in studying charitable donation, including endogeneity, saliency, and aggregation, while preserving the benefits of a naturally occurring framework. The richness of these data has already helped address key questions, such as the effect of price on charitable donations (Meer, 2014), the completion effect in the provision point mechanism (Argo et al., 2020), and the influence of matching grants on overall giving (Meer, 2017). We believe that crowdfunding presents promising new avenues for research.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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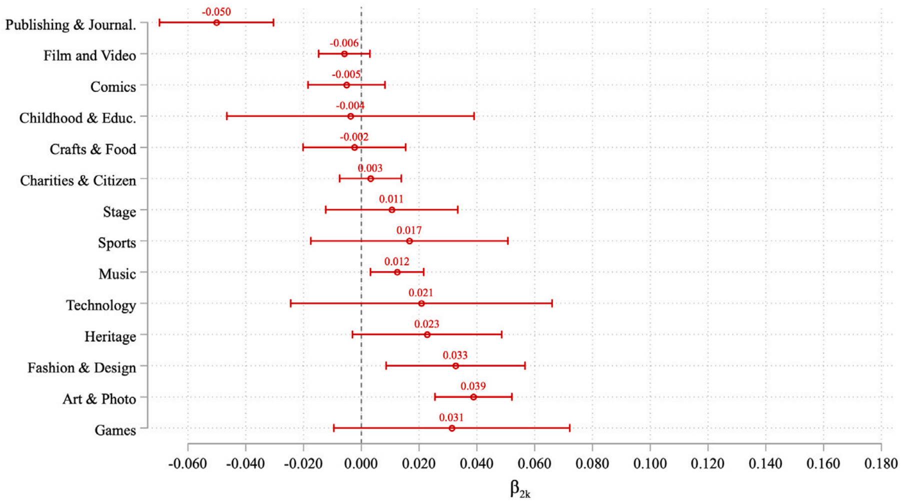
Appendix

A.1. Figures

(A) Below 100%



(B) Unique backers

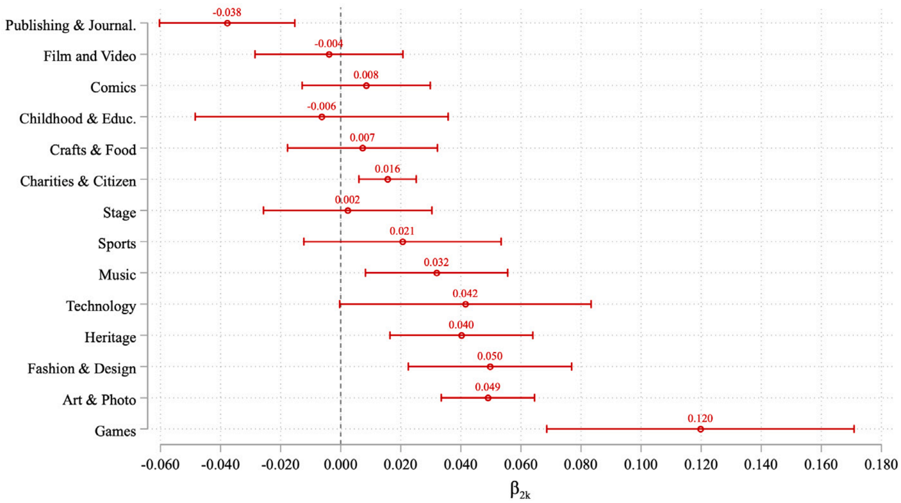


Fig. A.1. Average marginal effects β_{2k} by main category k. Panel A includes contributions made before the objective is reached, while Panel B includes contributions from unique backers.

Notes: The sample for Panel A includes 577,626 contributions from 464,770 backers across 14,211 projects, while Panel B includes 440,813 contributions from 440,813 backers across 13.508 projects. Each point represents the average marginal effect of $Log(C_{jt})$ for category k (β_{2k}) with a 95% CI, estimated using Eq. (1). The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. The specification includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors are clustered at the project level. The estimated model is presented in Table A.5 in Appendix.

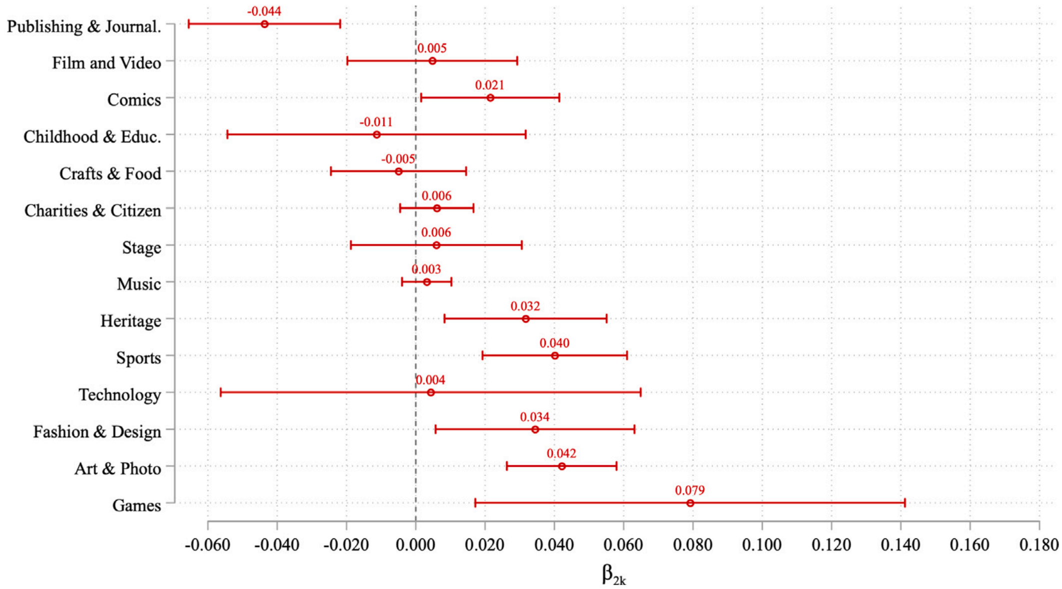
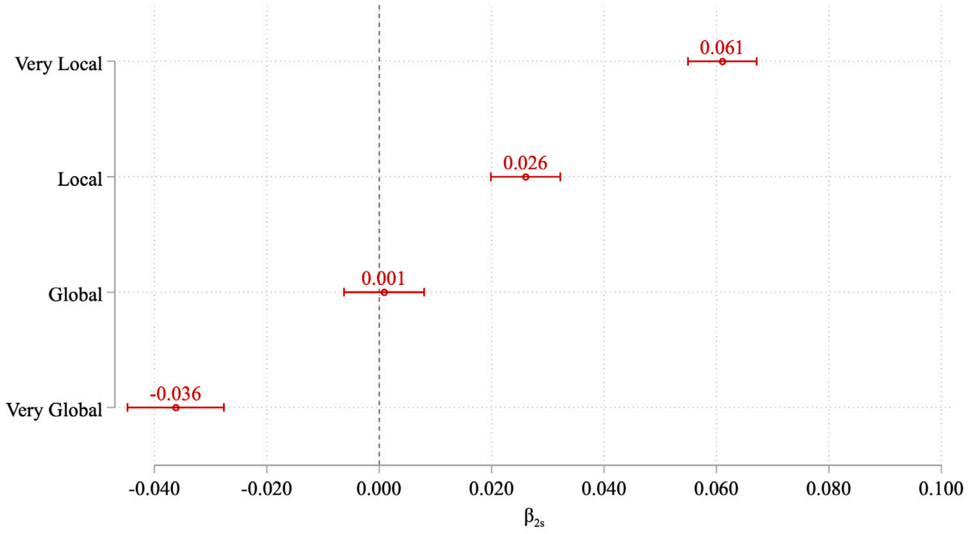


Fig. A.2. Average marginal effects β_{2k} by main categories excluding projects with depleted limited rewards.
Notes: The sample excludes projects in which at least one limited reward was depleted. It includes 634,056 contributions from 505,863 backers across 13,231 projects. Each point represents the average marginal effect of $Log(C_{jt})$ for main category k (β_{2k}) with a 95% CI using Eq. (1). The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. The specification includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors are clustered at the project level.

(A) BELOW 100%



(B) UNIQUE BACKERS

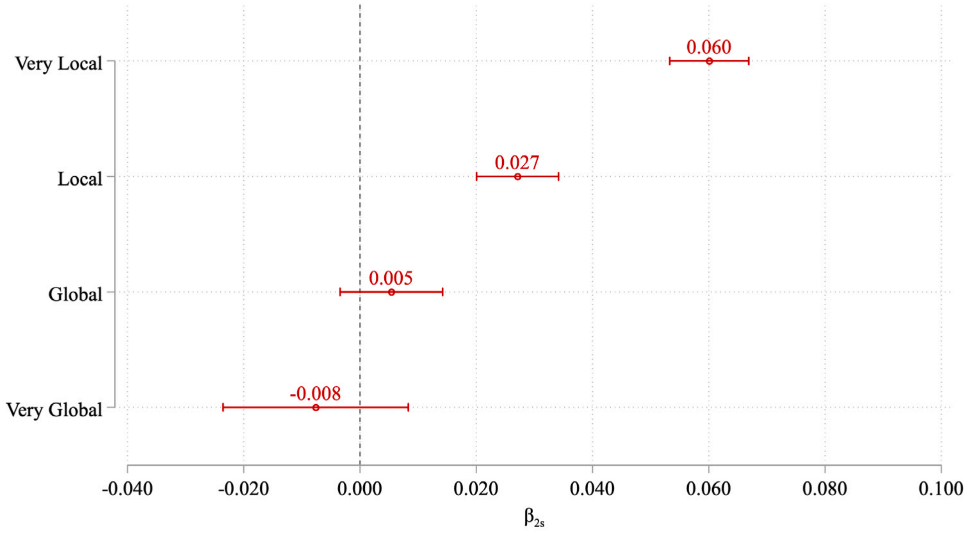


Fig. A.3. Average marginal effects β_{2s} by geographic scope. Panel A includes contributions made before the objective is reached, while Panel B includes contributions from unique backers.

The sample for Panel A includes 562,608 contributions from 453,433 backers across 13,523 projects, while Panel B includes 428,506 contributions from 428,506 backers across 12,848 projects. Each point represents the average marginal effect β_{2s} of $Log(C_{jt})$ by geographic scope s (from very local to very global) with a 95% CI using Eq. (2). The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. The specification includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors (in parentheses) are clustered at the project level.

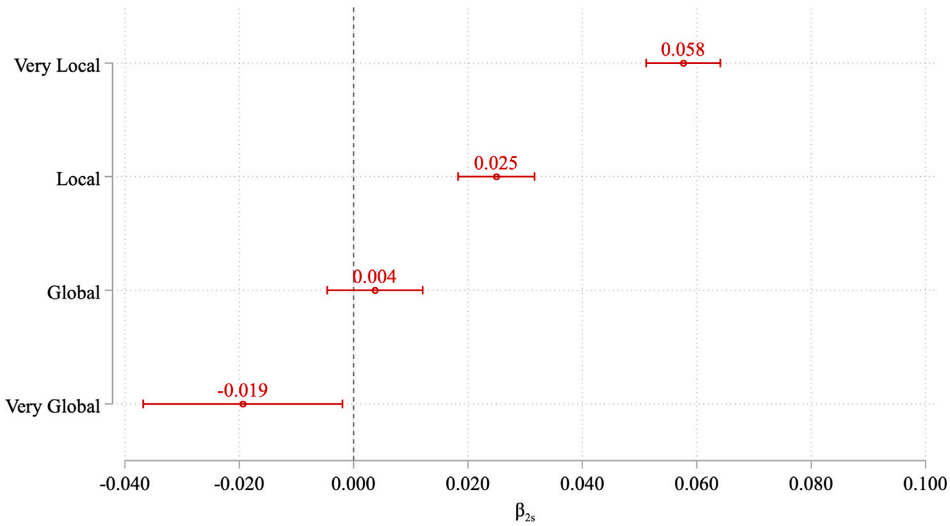


Fig. A.4. Average marginal effects β_{2s} by geographic scope excluding projects with depleted limited rewards.
Notes: The sample excludes projects in which at least one limited reward was depleted. The sample includes 611,832 contributions from 491,242 backers across 12,570 projects. Each point represents the average marginal effect β_{2s} of $Log(C_{jt})$ by geographic scope s (ranging from very local to very global) with a 95% CI using Eq. (2). The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. The specification includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors (in parentheses) are clustered at the project level.

A.2. Tables

Data availability

The authors do not have permission to share data.

Table A.1
Main categories of projects on Ulule.

Category	Part of projects	Description
Arts & Photos	5.63%	Artists and photographers seeking funding for exhibitions, installations, art/photo books, and limited-edition prints.
Charities & Citizens	20.60%	Nonprofits, activists, and social entrepreneurs funding humanitarian aid, sustainable development, animal welfare, education, and healthcare initiatives.
Childhood & Education	4.90%	Educators, activists, and nonprofits seeking funds for educational programs, school construction, and learning materials, particularly in underdeveloped regions.
Comics	2.47%	Independent artists and writers funding comic book series, anthologies, and graphic novels production and publication.
Crafts & Food	5.13%	Small entrepreneurs and artisans seeking funding for food/beverage production equipment and facilities, such as artisanal breweries and food trucks.
Fashion & Design	2.94%	Fashion designers and craftsmen funding clothing lines, accessories, and design items, often focusing on sustainable and innovative products.
Film & Video	17.81%	Independent filmmakers and production companies seeking funds for feature and short films, documentaries, animations, and web series, covering production through distribution costs, plus film festival initiatives.
Games	2.16%	Independent designers and small studios funding board games, video games, card games, and tabletop RPGs development and production.
Heritage	1.37%	Cultural organizations and community groups seeking funds to preserve and promote historical sites, digitize cultural artifacts, restore historical landmarks, and organize traditional cultural events and exhibitions.
Music	13.85%	Independent musicians, bands, and music educators funding albums, videos, concerts, tours, festivals, and music education programs.
Publishing & Journalism	5.42%	Independent authors, publishers, and journalists funding book production, magazine publishing, and digital content platforms.
Sports	7.29%	Athletes, teams, and sports organizations funding competition travel, training costs, event organization, and sports facility development.
Stage	8.57%	Artists, performers, and theater companies funding theater productions, concerts, dance shows, and comedy performances.
Technology	1.85%	Startups, entrepreneurs, and students funding hardware/software development, gadgets, mobile applications, and engineering projects.

Notes: This table presents the categories in our sample (N = 16,498). The column *Part of projects* indicates the proportion of each category relative to the total number of projects.

Table A.2
Sample summary statistics at the contribution level.

Variable	Obs	Mean	Std. Dev.	Min	Max	Median
Contribution level						
Contributed amount c (in euros)	926 515	45.69	94.45	1	10 000	25
Cumulative contributions C (in euros)	926 515	15 968.11	54 879.1	0	680 996	1855
Backer-owner distance (in km)	503 084	273.56	623.25	0	13 306.23	159.39
Joined Ulule for the project	926 515	0.68	0.47	0	1	1
Completed the campaign	926 515	0.01	0.09	0	1	0
No reward	926 515	0.20	0.40	0	1	0
Cash payment	926 515	0.00	.06	0	1	0
Project level						
Goal (in euros)	16 498	3085.4	5149.5	20	300 000	2000
Duration (in days)	16 498	40.98	12.25	19	72	40
Owner is a company	14 928	.1	.3	0	1	0
Owner is an individual	14 928	.54	.5	0	1	1
Owner is an association	14 928	.36	.48	0	1	0
Number of news	16 498	5.24	7.33	0	154	3
Number of subtags	16 498	1.78	1.21	0	5	2
Limited reward	16 287	.28	.45	0	1	0
Campaign in 2010	16 498	0	.01	0	1	0
Campaign in 2011	16 498	0	.01	0	1	0
Campaign in 2012	16 498	.06	.24	0	1	0
Campaign in 2013	16 498	.14	.35	0	1	0
Campaign in 2014	16 498	.25	.43	0	1	0
Campaign in 2015	16 498	.28	.45	0	1	0
Campaign in 2016	16 498	.27	.44	0	1	0
Per capita income (per year, in euros)	14 514	28 605.61	6864.51	19 620	42 458	26 055
Individual level						
Age	615 815	39.4	14.72	10	99	36
Number of projects backed	693 236	1.38	1.7	1	361	1

Contribution level: "joined Ulule for the project" is a dummy variable that equals 1 if the contribution date matches the date the backer created their Ulule account. "Completed the campaign" is a dummy variable that equals 1 if contribution c_i enables the project to reach its financial goal. The backer's age is computed based on their declared birth date, with values ranging from 10 to 90 years. The average income of the project owner's region in 2015 was obtained from the French National Institute of Statistics and Economic Studies.

Table A.3
Descriptive statistics by category.

	Arts & Photos	Charity & Citizens	Child. & Educ.	Comics	Crafts & Food	Fashion & Design	Film & Video	Games	Heritage	Music	Publish. & Journal.	Sports	Stage	Technology
Contribution level														
Contributed amount c (in euros)	45.69	46.16	42.27	36.53	52.14	55.31	45.47	61.07	62.50	40.23	41.72	50.68	44.44	54.59
	(85.24)	(104.00)	(86.48)	(46.95)	(111.27)	(105.05)	(100.67)	(86.41)	(141.60)	(86.29)	(82.11)	(103.58)	(88.80)	(130.69)
Cumulative contributions C (in euros)	2814.00	6459.36	4729.47	27 416.43	4145.40	3589.86	34 922.69	40 408.37	5733.51	9913.15	21 841.33	2771.39	2199.77	4386.24
	(4255.54)	(22934.78)	(10241.42)	(60209.13)	(5721.51)	(4720.40)	(100816.63)	(72830.10)	(7193.34)	(34304.73)	(46514.76)	(6106.29)	(3805.40)	(6043.16)
Backer-owner distance (in km)[a]	263.50	271.87	243.17	357.37	202.70	232.55	315.20	357.14	266.61	204.20	303.22	260.25	196.47	255.37
	(647.73)	(724.43)	(749.94)	(674.73)	(498.93)	(476.21)	(656.89)	(455.31)	(797.59)	(451.32)	(636.51)	(803.05)	(639.19)	(618.68)
Joined Ulule for the Project	0.68	0.72	0.74	0.47	0.71	0.71	0.71	0.38	0.71	0.71	0.63	0.81	0.74	0.70
	(0.47)	(0.45)	(0.44)	(0.50)	(0.46)	(0.46)	(0.45)	(0.49)	(0.46)	(0.45)	(0.48)	(0.39)	(0.44)	(0.46)
Completed the Campaign	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.01
	(0.10)	(0.10)	(0.11)	(0.07)	(0.09)	(0.09)	(0.10)	(0.06)	(0.09)	(0.09)	(0.07)	(0.11)	(0.10)	(0.08)
No reward	0.18	0.31	0.32	0.05	0.25	0.24	0.18	0.05	0.24	0.16	0.13	0.33	0.31	0.24
	(0.38)	(0.46)	(0.47)	(0.22)	(0.43)	(0.43)	(0.39)	(0.22)	(0.43)	(0.37)	(0.34)	(0.47)	(0.46)	(0.43)
Cash payment	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00
	(0.02)	(0.03)	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.21)	(0.04)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)
N	40 627	149 065	33 754	55 248	45 123	22 517	166 396	51 759	13 350	140 334	96 563	33 294	64 257	14 228
Project level														
Goal (in euros)	2683.11	2702.77	2593.06	3346.03	4063.10	3845.84	2879.42	5436.05	5836.09	2679.37	4955.18	2431.42	2762.44	4433.46
	(3311.54)	(4150.70)	(4052.69)	(3652.44)	(4555.32)	(3544.59)	(4271.53)	(8826.77)	(6210.53)	(2882.44)	(13805.12)	(3824.76)	(2840.23)	(5018.29)
Duration (in days)	38.88	40.61	40.88	41.93	42.39	41.32	39.11	41.46	47.15	42.25	41.39	42.73	41.04	41.21
	(12.07)	(12.29)	(12.32)	(11.85)	(12.02)	(11.72)	(12.45)	(12.36)	(12.12)	(12.10)	(11.99)	(11.86)	(11.89)	(12.88)
Owner is a company[a]	0.08	0.05	0.07	0.13	0.29	0.34	0.08	0.28	0.08	0.05	0.23	0.05	0.05	0.22
	(0.28)	(0.22)	(0.26)	(0.33)	(0.46)	(0.47)	(0.27)	(0.45)	(0.28)	(0.22)	(0.42)	(0.21)	(0.22)	(0.41)
Owner is an individual[a]	0.72	0.41	0.36	0.62	0.63	0.62	0.75	0.55	0.31	0.56	0.56	0.50	0.31	0.58
	(0.45)	(0.49)	(0.48)	(0.49)	(0.48)	(0.48)	(0.43)	(0.50)	(0.46)	(0.50)	(0.50)	(0.50)	(0.46)	(0.50)
Owner is an association[a]	0.19	0.54	0.57	0.25	0.08	0.04	0.17	0.17	0.61	0.39	0.20	0.46	0.64	0.21
	(0.40)	(0.50)	(0.50)	(0.43)	(0.27)	(0.19)	(0.37)	(0.38)	(0.49)	(0.49)	(0.40)	(0.50)	(0.48)	(0.41)
Number of news	5.34	3.76	4.11	13.80	5.83	5.36	5.66	12.76	7.18	5.21	7.82	2.46	4.31	4.91
	(6.64)	(5.20)	(5.80)	(14.54)	(6.80)	(6.21)	(7.37)	(15.27)	(7.30)	(7.02)	(8.29)	(4.39)	(5.50)	(6.10)
Number of subtags	2.52	2.60	2.53	2.21	2.63	2.73	1.89	2.50	2.43	1.95	2.36	2.15	2.11	2.54
	(0.74)	(0.68)	(0.70)	(0.84)	(0.73)	(0.61)	(0.92)	(0.76)	(0.79)	(0.87)	(0.83)	(0.85)	(0.89)	(0.75)
Limited rewards[a]	0.36	0.17	0.16	0.60	0.23	0.30	0.30	0.54	0.27	0.36	0.35	0.23	0.25	0.32
	(0.48)	(0.38)	(0.36)	(0.49)	(0.42)	(0.46)	(0.46)	(0.50)	(0.45)	(0.48)	(0.48)	(0.42)	(0.43)	(0.47)
Campaign in 2010	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Campaign in 2011	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Campaign in 2012	0.08	0.03	0.01	0.03	0.02	0.06	0.12	0.12	0.00	0.07	0.04	0.02	0.08	0.06
	(0.27)	(0.18)	(0.09)	(0.17)	(0.16)	(0.23)	(0.32)	(0.32)	(0.07)	(0.26)	(0.19)	(0.13)	(0.27)	(0.23)
Campaign in 2013	0.13	0.11	0.06	0.13	0.12	0.13	0.20	0.19	0.01	0.16	0.13	0.13	0.16	0.12
	(0.33)	(0.31)	(0.23)	(0.34)	(0.32)	(0.33)	(0.40)	(0.39)	(0.11)	(0.37)	(0.34)	(0.33)	(0.37)	(0.32)
Campaign in 2014	0.22	0.25	0.18	0.20	0.27	0.21	0.26	0.19	0.21	0.25	0.22	0.42	0.22	0.27
	(0.41)	(0.44)	(0.39)	(0.40)	(0.44)	(0.41)	(0.44)	(0.39)	(0.41)	(0.43)	(0.41)	(0.49)	(0.41)	(0.45)
Campaign in 2015	0.29	0.31	0.39	0.31	0.26	0.31	0.23	0.24	0.41	0.27	0.29	0.24	0.28	0.29
	(0.45)	(0.46)	(0.49)	(0.46)	(0.44)	(0.46)	(0.42)	(0.43)	(0.49)	(0.44)	(0.45)	(0.43)	(0.45)	(0.45)
Campaign in 2016	0.29	0.29	0.36	0.32	0.33	0.29	0.19	0.27	0.36	0.25	0.32	0.20	0.26	0.26
	(0.45)	(0.45)	(0.48)	(0.47)	(0.47)	(0.46)	(0.39)	(0.44)	(0.48)	(0.43)	(0.47)	(0.40)	(0.44)	(0.44)
Per capita income (per year, in euros)	28 368.31	28 125.40	27 336.68	27 304.12	26 540.81	29 015.42	31 182.23	28 053.94	27 503.33	28 258.86	28 403.95	26 946.66	29 444.49	29 029.88
	(6627.88)	(6449.03)	(5927.01)	(5949.11)	(5096.27)	(7104.93)	(7945.36)	(6174.90)	(6388.86)	(6656.49)	(6803.65)	(5102.04)	(7597.40)	(7251.28)
Obs	929	3399	808	408	847	485	2938	356	226	2285	895	1202	1414	306
Backer level														
Age[a]	39.82	40.78	41.79	35.84	38.72	37.69	36.12	35.05	46.50	38.82	41.24	39.32	42.10	36.08
	(14.38)	(15.61)	(14.01)	(12.26)	(13.45)	(13.33)	(14.55)	(10.90)	(15.31)	(13.99)	(14.29)	(14.32)	(14.82)	(13.67)
Number of projects backed	2.10	1.60	1.74	2.79	1.89	1.95	1.66	2.87	2.11	1.57	2.15	1.35	1.58	2.39
	(5.02)	(3.01)	(4.57)	(5.49)	(4.41)	(5.51)	(2.81)	(5.39)	(6.50)	(2.59)	(4.22)	(3.64)	(3.01)	(7.49)
Obs	36 222	130 700	31 128	38 896	40 840	20 358	142 025	29 476	12 116	121 970	81 499	31 000	57 381	13 103

[a] Notes: Variables are unavailable for all contributions, backers, or projects. The statistics are calculated based on the available data, with the number of observations determined from the most significant working sample. Note that backers who contributed to multiple projects may be included in various category samples.

Table A.4
Subtags by category.

	Arts & Photos	Charity & Citizens	Child. & Educ.	Comics	Crafts & Food	Fashion & Design	Film & Video	Games	Heritage	Music	Publish. & Journal.	Sports	Stage	Technology
Animation	0.02	0.05	0.13	0.02	0.04	0.01	0.08	0.07	0.08	0.08	0.02	0.06	0.13	0.02
Boardgames	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.59	0.00	0.00	0.01	0.00	0.00	0.01
Books	0.41	0.04	0.27	0.86	0.03	0.02	0.01	0.48	0.09	0.03	0.58	0.00	0.04	0.01
Childhood	0.02	0.23	0.86	0.07	0.05	0.07	0.04	0.04	0.03	0.04	0.10	0.10	0.13	0.02
Circus	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.12	0.01
Comics	0.01	0.00	0.00	0.27	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.00
Craftsmanship	0.10	0.04	0.02	0.03	0.59	0.49	0.01	0.01	0.22	0.04	0.02	0.02	0.03	0.04
DIY	0.03	0.03	0.02	0.02	0.13	0.11	0.02	0.05	0.00	0.11	0.03	0.01	0.03	0.12
Dance	0.03	0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.05	0.00	0.02	0.26	0.01
Design	0.15	0.02	0.02	0.02	0.07	0.50	0.01	0.10	0.04	0.01	0.03	0.00	0.01	0.11
Documentary	0.07	0.04	0.01	0.03	0.00	0.00	0.26	0.00	0.05	0.02	0.04	0.05	0.01	0.01
Fashion	0.02	0.01	0.00	0.00	0.06	0.73	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.02
Film & Video	0.02	0.01	0.00	0.00	0.00	0.00	0.59	0.00	0.00	0.05	0.05	0.01	0.03	0.06
Fine Arts	0.55	0.01	0.02	0.27	0.03	0.05	0.06	0.02	0.31	0.06	0.17	0.00	0.07	0.04
Food	0.02	0.03	0.00	0.00	0.46	0.01	0.00	0.00	0.01	0.00	0.04	0.00	0.01	0.02
Games	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.37	0.00	0.00	0.03	0.00	0.00	0.06
Green	0.06	0.30	0.11	0.02	0.35	0.15	0.07	0.01	0.16	0.02	0.06	0.07	0.03	0.14
Hacktivism	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.07
Heritage	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.20	0.00	0.01	0.01	0.02	0.00
Homeless WorldCup	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(mean) Humanitarian	0.01	0.40	0.16	0.00	0.01	0.01	0.02	0.01	0.00	0.01	0.02	0.16	0.02	0.01
Journalism	0.03	0.02	0.03	0.04	0.01	0.00	0.04	0.01	0.02	0.02	0.48	0.01	0.01	0.03
Music	0.02	0.01	0.01	0.00	0.01	0.01	0.04	0.02	0.00	0.55	0.05	0.00	0.12	0.03
Music video	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.26	0.00	0.02	0.02	0.00
Photography	0.61	0.02	0.02	0.01	0.02	0.02	0.07	0.00	0.04	0.03	0.13	0.02	0.02	0.05
Places	0.03	0.02	0.02	0.00	0.04	0.01	0.01	0.00	0.16	0.01	0.01	0.02	0.03	0.06
Politics	0.01	0.03	0.00	0.01	0.00	0.00	0.05	0.00	0.00	0.01	0.04	0.00	0.04	0.01
RPG	0.00	0.00	0.00	0.04	0.00	0.00	0.01	0.50	0.01	0.00	0.02	0.00	0.02	0.01
Solidarity	0.07	0.75	0.41	0.01	0.14	0.09	0.12	0.05	0.34	0.12	0.13	0.45	0.15	0.22
Sports	0.01	0.02	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.00	0.01	0.40	0.00	0.00
Stage	0.02	0.00	0.02	0.00	0.01	0.00	0.02	0.00	0.01	0.17	0.01	0.01	0.49	0.03
Technologeek	0.02	0.02	0.02	0.19	0.03	0.03	0.04	0.15	0.04	0.02	0.05	0.01	0.01	0.69
Travel	0.14	0.21	0.19	0.22	0.02	0.03	0.09	0.01	0.21	0.06	0.06	0.27	0.06	0.06
Weird	0.10	0.06	0.06	0.15	0.11	0.09	0.11	0.05	0.22	0.10	0.04	0.22	0.18	0.09
Entrepreneurship	0.06	0.13	0.05	0.00	0.46	0.36	0.04	0.03	0.11	0.04	0.13	0.10	0.01	0.44

Notes: Proportion of subtags within each project category.

Table A.5
Crowding out effect by main categories (OLS).

	(1)	(2)
	$logc_{ijt}$	
Constant	2.877***	−0.744***
	(0.052)	(0.278)
β_{1k} (Baseline: Art & Photos)		
Charities & Citizens	−0.000	0.195***
	(0.061)	(0.056)
Childhood & Educ.	0.026	0.209
	(0.128)	(0.140)
Comics	0.306***	0.251***
	(0.065)	(0.075)
Crafts & Food	0.255***	0.290***
	(0.087)	(0.088)
Fashion & Design	0.045	0.084
	(0.100)	(0.099)
Film & Video	0.239**	0.255***
	(0.103)	(0.089)
Games	−0.182	−0.154
	(0.139)	(0.149)
Heritage	0.106	0.081
	(0.099)	(0.090)
Music	0.058	0.023
	(0.071)	(0.092)
Publishing & Journalism	0.240***	0.383***
	(0.084)	(0.108)
Sports	0.050	0.201*
	(0.101)	(0.103)
Stage	0.175**	0.167*
	(0.088)	(0.086)
Technology	0.032	0.054
	(0.133)	(0.145)
β_{2k}		
Log_{jt}	0.073***	0.046***
	(0.009)	(0.007)
Charities & Citizen × Log_{jt}	−0.014	−0.043***
	(0.010)	(0.009)
Childhood & Educ. × Log_{jt}	−0.023	−0.055**
	(0.022)	(0.024)
Comics × Log_{jt}	−0.054***	−0.043***
	(0.010)	(0.011)
Crafts & Food × Log_{jt}	−0.037***	−0.046***
	(0.014)	(0.014)
Fashion & Design × Log_{jt}	0.004	−0.004
	(0.017)	(0.016)
Film & Video × Log_{jt}	−0.050***	−0.053***
	(0.017)	(0.014)
Games × Log_{jt}	0.034*	0.027
	(0.019)	(0.020)
Heritage × Log_{jt}	−0.003	−0.018
	(0.015)	(0.014)
Music × Log_{jt}	−0.025**	−0.020
	(0.012)	(0.015)
Publishing & Journalism × Log_{jt}	−0.047***	−0.074***
	(0.013)	(0.016)
Sports × Log_{jt}	−0.006	−0.028
	(0.018)	(0.018)
Stage × Log_{jt}	−0.038**	−0.041***
	(0.015)	(0.014)
Technology × Log_{jt}	−0.019	−0.021
	(0.023)	(0.025)

(*continued on next page*)

Table A.5 (*continued*).

Obs.	926 515	769 290
Clusters	16 498	14 217
R-squared	.025	.114
Time FE	No	Yes
Project level controls	No	Yes
Backer level controls	No	Yes

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents estimates from ordinary least squares regressions specified in Eq. (1). "Art and photos" is the baseline category k. The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. Column (1) is estimated without controls or fixed effects. The specification in column (2) includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors are clustered at the project level.

Table A.6
Crowding out for Publishing & Journalism and music projects.

	Publishing & Journalism (1)	Music (2)
	$logc_{ijt}$	
$LogC_{jt}$	0.008	−0.012***
	(0.011)	(0.005)
Journalism × $LogC_{jt}$	−0.047***	
	(0.018)	
Music concert × $LogC_{jt}$		0.026*
		(0.014)
Observations	56 378	119 764
Clusters	601	2000
R squared	.087	.107
Time FE	Yes	Yes
Project level controls	Yes	Yes
Backer level controls	Yes	Yes

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents estimates from ordinary least squares regressions on log-transformed contribution value c_{ijt} (dependent variable), winsorized at the 0.01 and 0.99 percentiles. The sample in columns (1) and (2) consists of contributions to projects in the main categories "publishing and journalism" and "music", respectively. Journalism is a dummy variable that equals 1 if a project is characterized by the subtag "journalism" (207 projects). "Music concert" is a dummy variable that equals 1 if the project title contains the word "festival" or "concert" (148 projects). All specifications include time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors (in parentheses) are clustered at the project level.

Table A.7
Crowding out effects by geographic scope (OLS)

	(1)	(2)
	$Logc_{ijt}$	
Constant	2.727***	−0.563
	(0.017)	(0.348)
β_{1s} (Baseline: Very Local)		
Local	0.180***	0.182***
	(0.026)	(0.025)
Global	0.303***	0.306***
	(0.030)	(0.030)
Very global	0.290***	0.352***
	(0.068)	(0.053)
β_{2s}		
Very Local × $LogC_{ij}$	0.090***	0.058***
	(0.003)	(0.003)
Local × $LogC_{ij}$	−0.028***	−0.033***
	(0.005)	(0.004)
Global × $LogC_{ij}$	−0.045***	−0.054***
	(0.005)	(0.005)
Very global × $LogC_{ij}$	−0.047***	−0.066***
	(0.010)	(0.008)
Observations	827 253	745 703
Clusters	13 941	13 529
R-squared	.014	.106
Time FE	No	Yes
Project level controls	No	Yes
Backer level controls	No	Yes

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents estimates from ordinary least squares regressions specified in Eq. (2). "Very local" is the baseline scope s. The dependent variable is the log-transformed contribution value c_{ijt}, winsorized at the 0.01 and 0.99 percentiles. Column (1) is estimated without controls or fixed effects. In column (2), the specification includes time-fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors (in parentheses) are clustered at the project level.

Table A.8
Interactions effect—Geographic scope.

	(1)	(2)	(3)
	$logc_{ijt}$		
$LogC_{jt}$	0.018***	0.012***	0.007*
	(0.003)	(0.004)	(0.004)
$LogC_{jt} \times Scope_{max}$	−0.003**		
	(0.001)		
$LogC_{jt} \times Scope_{p99}$		−0.005***	
		(0.001)	
$LogC_{jt} \times Scope_{p98}$			−0.002**
			(0.001)
Observations	745 703	745 703	745 703
Clusters	13 529	13 529	13 529
R-squared	.106	.105	.105
Time FE	Yes	Yes	Yes
Main category FE	Yes	Yes	Yes
Project level controls	Yes	Yes	Yes
Backer level controls	Yes	Yes	Yes

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents estimates from ordinary least squares regressions on log-transformed contribution value c_{ijt} (dependent variable), winsorized at the 0.01 and 0.99 percentiles. All specifications include time and main category fixed effects. We control for project-level variables (log(income$_j$), log(goal), duration (in days), number of subtags, number of news, limited-stock rewards, owner type), backer-level variables (log(age) and number of projects backed), and contribution-level variables (completed the campaign, joined Ulule for the project, no reward, and cash payment). Standard errors (in parentheses) are clustered at the backer level.

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