AMERICAN MARKETING ASSOCIATION

Article

Journal of Marketing
1-18

DOI: 10.1177/00222429211031814
journals.sagepub.com/home/jmx
SAGE

Do Backer Affiliations Help or Hurt Crowdfunding Success?

Kelly B. Herd, Girish Mallapragada, and Vishal Narayan

Abstract

Crowdfunding has emerged as a mechanism to raise funds for entrepreneurial ideas. On crowdfunding platforms, backers (i.e., individuals who fund ideas) jointly fund the same idea, leading to affiliations, or overlaps, within the community. The authors find that while an increase in the total number of backers may positively affect funding behavior, the resulting affiliations affect funding negatively. They reason that when affiliated others fund a new idea, individuals may feel less of a need to fund, a process known as "vicarious moral licensing." Drawing on data collected from 2,021 ideas on a prominent crowdfunding platform, the authors show that prior affiliation among backers negatively affects an idea's funding amount and eventual funding success. Creator engagement (i.e., idea description and updates) and backer engagement (i.e., Facebook shares) moderate this negative effect. The effect of affiliation is robust across several instrumental variables, model specifications, measures of affiliation, and multiple crowdfunding outcomes. Results from three experiments, a survey, and interviews with backers support the negative effect of affiliation and show that it can be explained by vicarious moral licensing. The authors develop actionable insights for creators to mitigate the negative effects of affiliation with the language used in idea descriptions and updates.

Keywords

backer affiliation, crowdfunding, prosocial, social structure, vicarious moral licensing

Online supplement: https://doi.org/10.1177/00222429211031814

Crowdfunding has emerged as a dominant mechanism to harness the power of crowds in raising funds for innovative ideas. Interest in crowdfunding has surged in recent years. Facebook acquired Oculus 3D visualization device, a crowdfunded idea on Kickstarter, for US$3 billion (Durbin 2017). Peloton, the highly successful exercise bike, started as a Kickstarter project. The global crowdfunding market is expected to be well over US$40 billion by 2026 (Statista 2021). Brands such as GE (Cowley 2016) and Unilever use crowdfunding to spur innovation (Stalder and Stenson 2016), and academic research on the phenomenon and its role in the digital economy is emerging (Allen, Chandrasekaran, and Basuroy 2018; Dai and Zhang 2019). Crowdfunding is a form of crowdsourcing in which participants, hereinafter referred to as "backers," are recruited to raise funds for ideas (e.g., Fan, Gao, and Steinhart 2020; Wei, Hong, and Tellis 2021). As some backers fund the same ideas (i.e., "cobacking"), overlaps develop between these backers. These overlaps, called "affiliations," are key building blocks of the community's network structure and have been studied in other crowdsourcing communities (e.g., Ransbotham, Kane, and Lurie 2012). In this research, we explore how affiliation, defined as the number of cobacking relationships between potential backers and those who have previously funded the focal idea, might affect the idea's crowdfunding success. We illustrate affiliation in crowdfunding using a stylized example in Figure 1.

We know that crowd size affects outcomes positively as participants look to anonymous others for cues to decide which ideas to fund, a phenomenon referred to as "herding" (e.g., Zhang and Liu 2012). Previous research shows that attracting more backers positively impacts crowdfunding outcomes (Hou, Li, and Liu 2020), an insight that many creators seem to grasp. However, crowd size does not represent the

Kelly B. Herd is Assistant Professor of Marketing, School of Business, University of Connecticut, USA (email: kelly.herd@uconn.edu). Girish Mallapragada is Associate Professor of Marketing, Weimer Faculty Fellow, Kelley School of Business, Indiana University, USA (email: gmallapr@indiana.edu). Vishal Narayan is Associate Professor of Marketing, NUS Business School, Singapore (email: bizvn@nus.edu.sg).

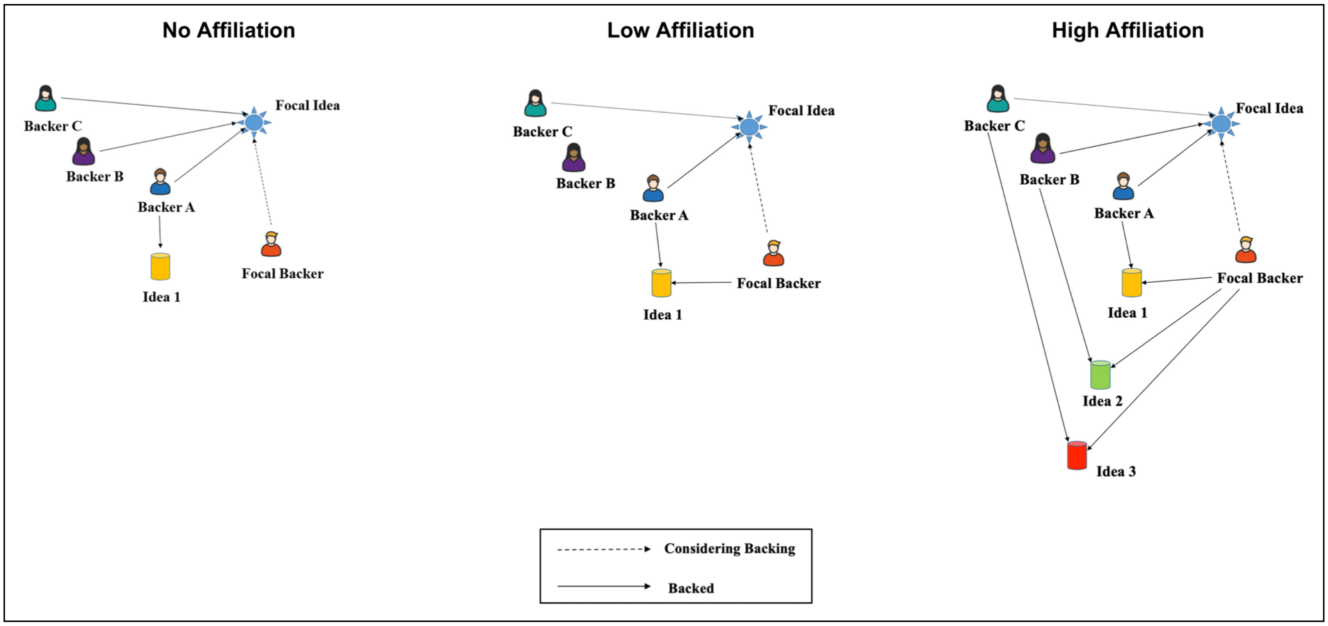

Figure 1. Illustration of affiliation in crowdfunding.
Notes: The figure represents simplified examples of three levels of affiliation (no affiliation, low affiliation, and high affiliation) for a focal backer. In all three scenarios, backers A, B, and C have already funded a focal idea. Subsequently, a new backer, labeled "focal backer," also funds the focal idea. This is where the affiliation for the focal backer is formed. In the first scenario, the focal backer has never jointly funded an idea with any of these three backers (no affiliation). In the second scenario, the focal backer and backer A have previously jointly funded idea 1 (low affiliation). In the final scenario, the focal backer has jointly funded with each of the three backers, leading to the highest level of affiliation. We propose that affiliation between the focal backer and others will influence the amount that the focal backer puts toward the focal idea.

social structure (i.e., the pattern of connections in the community). In crowdfunding, as in other contexts in which shared communal goals exist (e.g., Wikipedia), social structure plays a more prominent role (e.g., Ransbotham, Kane, and Lurie 2012; Wei, Hong, and Tellis 2021).

Our primary contribution is in showing that while the total number of backers (i.e., crowd size) may positively affect funding behavior and idea success (e.g., Zhang and Liu 2012), adding backers may not be unilaterally beneficial as the ensuing affiliation between backers negatively affects funding. Our analysis reveals that the negative effect of backer affiliation is above and beyond the positive effect of number of backers (i.e., the herding effect), highlighting the tension between the benefits of adding more backers and the adverse effects of backer affiliation. In other words, while adding a new backer (e.g., the focal backer in Figure 1) may positively affect the focal idea's success, adding this focal backer may not be *equally* beneficial across the three scenarios in Figure 1 as the degree of affiliation differs. We propose that the affiliation between the focal backer and other backers will influence the amount that the focal backer puts toward the focal idea and, thus, the idea's funding success.

Affiliation is a powerful force because it makes affiliated others' actions lead to changes in one's subsequent behavior (e.g., Mallapragada, Grewal, and Lilien 2012; Sunder, Kim, and Yorkston 2019). In some contexts, affiliation *positively* affects behavior as individuals desire to belong and therefore conform to affiliated others' behavior (e.g., Leary 2010). However, in crowdfunding communities where individuals are often motivated by prosocial goals (e.g., Simpson et al. 2021), we propose that such affiliation can *negatively* affect behavior. When individual actions benefit a social cause, seeing affiliated others participate may make individuals feel less of a need to do so, a process referred to as "vicarious moral licensing" (e.g., Decety and Grèzes 2006; Goldstein and Cialdini 2007; Meijers et al. 2019). Thus, we propose that when backers decide whether to fund an idea, they are less likely to do so or more likely to fund a lower amount if affiliated others have already done so.

While affiliations develop in the community through cobacking, creators and backers also engage through nonmonetary actions, thereby driving social interaction. Therefore, to develop further substantive implications about the effect of affiliation, we examine the moderating role of both creator and backer engagement (e.g., Bayus 2013; Mallapragada, Grewal, and Lilien 2012). For example, creators communicate with backers through the description of the idea on its homepage, perceived to be an important determinant of an idea's success (Moradi and Dass 2019; Xiang et al. 2019), and by posting updates about progress. Backers engage with the community by sharing ideas on social media. We aim to understand how the effect of affiliation varies due to creator and backer engagement, as they help shed light on the underlying mechanism that drives the effect of affiliation.

We use multiple methods and data sets, including secondary data and experiments, to provide convergent validity to our findings. We also conduct interviews with 6 backers, survey 100 backers, and analyze 572 posts on backer forums to develop insights about the mechanism driving the effect of affiliation on funding outcomes. First, we assemble a comprehensive data set of daily funding for 2,021 new crowdfunded ideas listed on Kickstarter. We study two crowdfunding outcomes: (1) the monetary amount of funding received by an idea on any given day and (2) whether the idea raises sufficient funds during the funding window to meet or exceed its funding goal. We measure affiliation of an idea on the focal day as the number of cobacking relationships of backers who back on the focal day, with backers who funded until the day before the focal day (e.g., Mallapragada, Grewal, and Lilien 2012; Narayan and Kadiyali 2016). We estimate an instrumental variables regression model with fixed effects to assess the impact of affiliation among an idea's backers on the daily funding amount and report results from several robustness analyses. Second, we present results from controlled experiments, where we exogenously manipulate affiliation, and across three experiments, we replicate the negative effect of affiliation on funding, examine the underlying mechanism, and uncover the role of a key moderator. We find that the negative effect is stronger when creators use more communal words—both in the initial description of the idea and in subsequent updates—and when more backers share the idea on social media. Thus, creator and backer engagement may moderate prosocial motives to fund, further validating the proposed licensing mechanism.

We make several contributions. We are the first to show that affiliation among backers affects crowdfunding success in statistically and economically significant ways after controlling for herding and accounting for several alternative explanations. A 10% daily increase in number of backers would lead to an additional 20.2% in funding or an increase of US$83/day (i.e., the herding effect). In contrast, a 10% daily increase in backer affiliation would lead to an 8.7% decrease in funding or a decrease of US$36/day, offsetting the increase due to number of backers by about 43%. Thus, adding backers is good, but if the additional backers increase affiliation, the positive effect of adding these backers is smaller in the scenario where affiliation is high. We isolate vicarious moral licensing as a theoretical mechanism that drives the negative effect of affiliation through experiments. We explore the role of factors related to the idea, the creator, and the backers, all of which interact with affiliation.

Theoretical Background

Social Influences in Crowdfunding

Although crowdfunding has emerged as a dominant force for funding new ideas, research on crowdfunding is limited. Most early research focuses on microlending (Lin, Prabhala, and Viswanathan 2013; Zhang and Liu 2012) or on crowdfunding platforms for music and journalism (e.g., Agrawal, Catalini, and Goldfarb 2015; Burtch, Ghose, and Wattal 2013). Topics such as proximity to the deadline (Dai and Zhang 2019) and the text of content (e.g., Netzer, Lemaire, and Herzenstein 2019) have also garnered attention. Researchers have studied a variety of social factors that influence crowdfunding, in particular, the relationship between creators and individual backers, including the role of offline friendship (Lin, Prabhala, and Viswanathan 2013), geographic proximity (Agrawal, Catalini, and Goldfarb 2015), and social interactions (Kim et al. 2020). We present a summary of representative research in Table 1.

In addition to the relationship between creators and backers, there are several ways in which others' actions might inform backers' funding decisions. For example, Zhang and Liu (2012) report that potential lenders assess borrowers' creditworthiness by observing other lenders. They attribute the positive effect of the number of other lenders to herding, wherein crowd size becomes a beacon for others to decide which ideas to fund. This finding might suggest that the mere addition of more supporters unilaterally benefits crowdfunding outcomes as potential backers simply follow other backers. What are some factors that might limit the positive impact of the crowd's behavior on crowdfunding? To answer this question, we note that most research has considered the presence of the anonymous crowd as the cause for a social effect that is generally positive. However, crowd size does not account for an important aspect of networks (i.e., the structure of connections among the community's participants).

Thus, what is missing in extant research is an explicit acknowledgment of social structure beyond crowd size and an exploration of how it impacts crowdfunding outcomes. Social structure arises due to coparticipation in events, in our case, cobacking across ideas, a phenomenon referred to as affiliation (e.g., Faust 1997; Wasserman and Faust 1999). Affiliation, identified as an important phenomenon in the new digital economy dominated by crowdsharing (Eckhardt et al. 2019), is the central focus of our research.

Affiliation in Crowdfunding

Communities evolve through repeated interactions between members, which give rise to affiliations or overlaps. As affiliations grow, the interconnectivity among backers leads to scaffolding structures that hold the community together through both first- and second-order ties. Affiliations have been studied in interfirm relationships (Swaminathan and Moorman 2009), board interlocks (Srinivasan, Wuyts, and Mallapragada 2018), product development (e.g., Mallapragada, Grewal, and Lilien 2012), and wiki contributions (Ransbotham, Kane, and Lurie 2012). Regardless of the context, research suggests that (1) individuals notice affiliated others' behavior, (2) individuals feel a sense of connectedness and shared identity with affiliated others, and as such, (3) affiliated others' actions lead to changes in one's subsequent behavior (e.g., Mallapragada, Grewal, and Lilien 2012; Sunder, Kim, and Yorkston 2019).

To establish that participants notice affiliated others' behavior when visiting crowdfunding platforms, we ran a pilot study with actual backers prescreened on the basis of their prior crowdfunding behavior. Participants were shown a screenshot of a crowdfunding page created by a web designer. To assess which information captured participants' attention, we used a

Table 1. Comparison with Relevant Empirical Research.

References (Published)	Dependent Variables	Explanatory Variables	Empirical Model Features	Data Context	Experiments	Findings
Our research	Funding	• Affiliation • Mediator: vicarious moral licensing • Moderators: creator and backer engagement	• Fixed-effects log-linear regression • Endogeneity (instrument) • Robustness checks: probit, logit, and Tobit	Crowdfunding (Kickstarter, experiments)	Three experiments	Prior backer affiliation decreases funding; the negative effect is due to vicarious moral licensing. This effect is stronger for ideas with communal descriptions, more communal updates, and more backer sharing on social media.
Wei, Hong, and Tellis (2021)	Success of funding	• Similarity between ideas	• Network similarity • Binary regression	Crowdfunding (Kickstarter)	No	Prior success of similar ideas affects success. Funding performance increases as an idea's novel and imitative characteristics are balanced. The optimal funding level is closer to the level of similar ideas.
Netzer, Lemaire, and Herzenstein (2019)	Loan payback	• Loan description	• Text analytics • Binary regression	Crowdlending (Prosper)	No	Borrowers who use certain types of words are more likely to default.
Dai and Zhang (2019)	Funding time elapsed	• Going past deadline • Prosocial motivation • Creator is individual	• Regression continuity	Crowdfunding (Kickstarter)	No	Backers might be driven by prosocial motives around deadline following goal pursuit.
Kim et al. (2020)	Goal completion	• Forward looking • Social interactions	• Bayesian IJC method • Two-step • Counterfactuals	Crowdfunding (music) (Sellaband)	No	Forward-looking investment behavior as well as contemporaneous and forward-looking social interactions impact share purchases and goal completion.
Burtch et al. (2013)	Contributions	• Concealment • Social norms	• Tobit • Endogeneity (IV)	Crowdfunding (Data set undisclosed)	No	Concealment hurts the likelihood of contribution and contribution. Social norms drive concealment.
Agrawal, Catalini, and Goldfarb (2015)	Decision to invest	• Geography	• Linear regression • Fixed effects	Crowdfunding (music) (Sellaband)	No	Local backers are not influenced by artist. The effect does not persist past the first investment, indicating the role of search but not monitoring.
Burtch et al. (2013)	Contribution frequency	• Crowding • Funding window • Degree of exposure	• Log-linear regression • Endogeneity (GMM)	Crowdfunding (journalism) (Data set undisclosed)	No	Partial crowding-out effect. Backers experience lower marginal utility of giving as the funds become less relevant to the recipient. The funding window and degree of exposure have a positive effect, after publication of the story.
Lin, Prabhala, and Viswanathan (2013)	Interest rate, default rate	• Friendships	• Probit regression	Crowdlending (Prosper)	No	Online friendships act as signals of credit quality, increase the probability of funding, lower interest rates, and result in lower ex post default rates—gradation in effects based on roles and identities of friends.
Zhang and Liu (2012)	Loan amounts	• Crowding	• Hazard model • Fixed effects • First differences	Crowdlending (Prosper)	No	Well-funded borrowers attract more funding. Lenders learn from peer decisions and do not mimic.

Notes: IV = instrumental variable, GMM = generalized method of moments; IJC = Imai, Jain, and Ching (2009).

standard heat-mapping approach for measuring visual attention (Berger et al. 2012). Invisible boxes around various pieces of information (e.g., idea title, backer information, idea description) coded visual attention as participants read and clicked on information, as per instructions. We found that many participants read and clicked on backer information, more so than other potentially relevant information such as the number of shares and creator information. Further, of the available backer information, affiliation ranked as highly important (for details, see Web Appendix A). Discussions on crowdfunding message boards and websites, as well as results from a survey that we conducted (discussed in the following sections), further support this idea, suggesting that among all available information, backers do consider affiliated others' behavior as they make funding decisions. Next, to confirm that affiliation affects perceptions of connectedness and shared identity in crowdfunding communities, we ran a pilot study with 150 Amazon Mechanical Turk (MTurk) participants. We find that affiliation significantly increased perceptions of connectedness and shared identity with other backers (see Web Appendix B).

If potential backers notice affiliated others' behaviors and feel a sense of connectedness with these affiliated others, how might affiliated others' behavior influence their own funding decisions? To answer this important question, we next examine crowdfunding platforms and how they differ from noncommunal (i.e., transactional) contexts.

Vicarious Moral Licensing in Crowdfunding Communities

Crowdfunding is a communal endeavor in which individuals collaborate to achieve shared goals, and platforms grow due to members' participation and interactions (Simpson et al. 2021). Individuals behave differently in communal contexts than in noncommunal (i.e., transactional) contexts (e.g., Clark and Mils 1993; Fiske 1992). For example, in communal contexts, individuals are more likely to request help from others, keep track of others' needs, respond to them, and report more positive emotions while doing so (Fiske 1992). In crowdfunding, these prosocial goals are reflected in the desire to help others, achieve funding goals, and be part of a community (Gerber and Hui 2014).

In crowdfunding communities where individuals are often motivated by prosocial goals (e.g., Simpson et al. 2021), we propose that seeing affiliated others fund may make individuals feel less of a need to do so, a process referred to as vicarious moral licensing (e.g., Decety and Grèzes 2006; Goldstein and Cialdini 2007; Meijers et al. 2019). Vicarious moral licensing occurs when individuals see affiliated others' actions as satisfying their own goals, which changes their perceived moral imperative and subsequent behavior. For example, learning that affiliated others demonstrate environmentally friendly behavior makes individuals less likely to do so (Meijers et al. 2019). It is important to recognize that this effect is not merely akin to strangers' behavior in a crowd (i.e., the bystander effect; e.g., Kuppuswamy and Bayus 2017), but that it is those with whom an individual perceives a social connection (i.e., affiliation) that drives the focal effect.

To confirm the importance of affiliated others' behavior and further validate the proposed mechanism, we conducted in-depth interviews of 6 backers, surveyed 100 backers, and coded 572 posts from KickstarterForum.org, the dominant crowdfunding discussion forum (see Web Appendix C). The findings confirmed the prominence of prosocial (i.e., communal) motives on crowdfunding decisions, the importance of affiliated others' behavior on backers' own funding behavior, and the role of vicarious moral licensing. For example, as one interview participant explained, "I look at other funders only to further discover related projects. It's an interesting way to discover—because some people are more involved than you are.… It's interesting to follow that rabbit trail and see, 'Oh, this person supported this, and look at what else they fund.'" Another stated, "You are dealing with finite resources in terms of what you are willing to spend. If you support one thing, I don't know, for me, if I see someone supporting something else, I think, well yeah, they supported that. I'm sure I could find a bunch of other people that support a bunch of other things. I just gave X amount of dollars, whatever amount I have, and I'm not going to be giving any more than that right now."

Although we propose vicarious moral licensing as the mechanism underlying the focal effect of affiliation and initial evidence indicates this to be the case, we acknowledge the complexity of social interactions in crowdfunding. Because these social interactions are likely to be subject to several factors, we consider uniqueness as an alternative explanation for the negative effect of affiliation on funding. Backers may try to identify ideas that have received less funding from affiliated others. By doing so, backers can distinguish themselves from these affiliated others, fulfilling a need for uniqueness (e.g., Tian et al. 2001). In our analysis, we report results from an experiment where we test vicarious moral licensing and uniqueness as potential explanations for the negative effect of affiliation on funding.

Moderators of the Effect of Affiliation on Crowdfunding Success

Crowdfunding platforms are characterized by contributions from both creators and backers (e.g., Bayus 2013; Ransbotham, Kane, and Lurie 2012) as these interactions create and sustain the community's viability. Therefore, we explore the role of creator and backer engagement in moderating the impact of affiliation on crowdfunding.

Previous research has found that while prosocial goals may be common in crowdfunding platforms (e.g., Simpson et al. 2021), an idea's description can further induce prosocial motivation and behavior when it emphasizes communal language (Hong, Hu, and Burtch 2018). We propose that the vicarious moral licensing effect (i.e., the negative effect of affiliation on funding) is driven by the communal context and the prosocial behavior it prompts and that this behavior is further heightened by creators describing their ideas with communal words like “together” and asking backers to “partner” with them by providing financial “support” (Pietraszkiewicz et al. 2017). As such, ideas described with more (vs. less) communal words will exhibit a stronger negative effect of affiliation on funding outcomes.

Creators can also engage with the backer community by posting updates to highlight their strategic goals and the idea’s progress. Updates provide diagnostic information concerning an idea’s success (e.g., Bayus 2013; Mallapragada, Grewal, and Lilien 2012). Updates might draw backers’ attention to the idea’s characteristics and evolution, and lessen attention toward cobackers and affiliation. Consistent with the vicarious moral licensing mechanism, we expect updates that use more (vs. less) communal words to strengthen affiliation’s negative effect. As such, we estimate the moderating effects of communal words in the creator’s updates.

We also explore how backers’ engagement might moderate the affiliation effect by exploring the role of social media sharing of the focal idea by backers. While sharing behavior on social media could have several motivations, altruism is perceived as a primary motivator, and others seeing the shares likely view them as such (Kim and Yang 2017; Li and Wang 2019). We expect that such sharing heightens funders’ prosocial motives and vicarious moral licensing, further strengthening the negative effect of affiliation. Next, we describe our data and methodology.

Data and Methodology

We employed a multimethod approach to investigate the phenomenon. We collected and analyzed two types of data: observational data from a crowdfunding platform and experimental data from lab settings. We begin by describing the observational data, the empirical model and identification strategy, the results, and robustness checks. Then, we describe three experiments in which we identify the primary effect in a controlled setting and shed light on the mechanism underlying the primary effect and its moderator. The first experiment demonstrates the negative effect of affiliation on funding behavior. The second experiment validates vicarious moral licensing as an underlying mechanism and rules out uniqueness as one potential alternative explanation. The third experiment examines how the idea’s description moderates the effect of affiliation.

Collection and Analysis of Observational Data

We collected data on Kickstarter, the world’s largest and most prominent crowdfunding platform. We utilized a web crawler to visit the new ideas page listed on Kickstarter beginning December 18, 2013. From that day and every subsequent day of data collection, the crawler visited the pages of the ideas that were started on the first day of the crawl, in addition to all the ideas that were started on the subsequent days. We stopped the crawler after 37 days, giving us data on 2,021 new ideas. We acknowledge that our research’s funding constraints affected the number of days, but we went one week past the most common deadline of 30 days. We note that while some ideas in our sample received funding after data collection stopped, our results are robust to this truncation.[1]

For the data collection, the crawler began with ideas that started receiving funds on the day of the crawl, and it identified every backer who funded the focal idea, the funded amount, and the calendar date. The crawler then visited every backer’s history and collected information on all the other ideas that the backer had funded in the past. At the time of data collection, Kickstarter made all backers visible to all prospective backers. The list of backers on Kickstarter was available by clicking the “community” link that prominently appears on the focal idea’s web page.[2] This process allowed us to construct the network, giving us the structure of relationships to calculate affiliation. The crawler also collected other relevant information from the page, including the idea’s description, number and text of updates, and the number of Facebook shares of the idea to measure backer engagement.

Our unit of analysis for the daily amount funded is an idea-day, and our final sample had 32,438 observations at the idea-day level. This specification makes the most sense because, for a data set with idea-day-backer as the unit of analysis, the funded amount (for an idea on a day) takes zero values for over 99.9% of observations, making such a specification noninformative. Next, we describe the key measures.

Daily amount funded. Consistent with prior literature (Agrawal, Catalini, and Goldfarb 2015; Burtch, Ghose, and Wattal 2013), our funding success measure is the amount of funding received by an idea on any given day. Across all crowdfunding platforms, this measure is always easily and prominently visible on the idea’s webpage. Subsequently, we show that our results are robust to other measures of success.

Affiliation. Consistent with prior literature (e.g., Mallapragada, Grewal, and Lilien 2012; Narayan and Kadiyali 2016), we posit that two backers are affiliated if they have funded at least one common idea on the platform and are not affiliated if all the ideas that they have funded are mutually exclusive. Thus, the backer affiliation for a focal idea on a focal day is the number of cobacking relationships between those backers who fund the focal idea *on* the focal day and all backers who have funded the focal idea at any time *before* the focal day.

Consider a backer of a focal idea who funds the focal idea on the focal day. Consider another backer of the focal idea who funds the focal idea any time before the focal day. A cobacking relationship exists between these two backers if they have both funded one idea (other than the focal idea) any time before the focal day. One cobacking relationship represents one unit of affiliation. Affiliation increases both with the number of backers who coback and with the number of cobacked ideas.

[1] Results for this analysis are available from the authors upon request.
[2] On many platforms, such information is readily available on the idea’s home page (e.g., https://gogetfunding.com, https://www.piggybackr.com).

Table 2. Summary Statistics for Kickstarter.

Variable	Mean	SD	Min	Median	Max
Amount of funding of idea i (in \$) on day t	409.34	4,764.72	0	0	593,731
Backer affiliation of idea i by day t − 1 ($Affil_{it-1}$)	3.33	10.66	0	0	477
Cumulative number of backers funding idea i by day t − 1 ($CumBackers_{it-1}$)	53.85	357.87	0	10	17,018
Number of backers funding idea i on day t − 1 ($Backers_{it-1}$)	6.71	142.99	0	1	17,010
Cumulative number of updates by creator of idea i by day t − 1 ($CumUpdates_{it-1}$)	8.82	23.64	0	0	524
Proportion of funding goal of idea i achieved by day t − 1 ($PropGoal_{it-1}$)	.49	2.14	0	.13	132.63
Proportion of funding duration of idea i completed by day t − 1 ($PropDuration_{it-1}$)	.31	.24	0	.27	.97
Closeness centrality of idea i as of day t − 1	5.67×10^{-9}	5.01×10^{-8}	3.49×10^{-11}	2.50×10^{-10}	2.2×10^{-6}
Betweenness centrality of idea i as of day t − 1	1,258.07	8,698.49	0	0	335,213
Eigenvector centrality of idea i as of day t − 1	.002	.03	0	2.50×10^{-9}	1
Last week (1 if day t is in the last week of funding of idea i, 0 otherwise)	.08	.28	0	0	1
Cumulative number of communal words in updates by creator of idea i by day t − 1 ($CommunalUpdates_{it-1}$)	20.17	1,696.27	0	0	230,232

To elaborate, consider the following examples. In each example, idea i is launched on day $t = 1$, say December 13. Further, Jack funds idea i on December 17 ($t = 5$), and the goal is to calculate affiliation as of December 17 ($t = 5$).

Example 1: Tom funds idea i on December 13. Also, before December 17, Jack and Tom both fund another idea j. As there is one cobacking relationship (that between Jack and Tom for cobacking idea j), $Affiliation_{i,\ t=5} = 1$.

Example 2: Tom funds idea i on December 13. Jack and Jill both fund idea i on December 17. Before December 17, Jack and Tom both fund another idea j. Furthermore, before December 17, Jill and Tom both fund another idea k. As there are two cobacking relationships (those between Jack and Tom for cobacking idea j, and between Jill and Tom for cobacking idea k), $Affiliation_{i,\ t=5} = 2$.

Example 3: Tom funds idea i on December 13. Jane funds idea i on December 14. Before December 17, Tom, Jack, and Jane funded another idea j. As there are two cobacking relationships (those between Jack and Tom for cobacking idea j, and between Jack and Jane for cobacking idea j), $Affiliation_{i,\ t=5} = 2$.

We present summary statistics for Kickstarter in Table 2. The median number of backers who fund an idea in a day is 1, and most ideas have only a few backers. When a backer funds an idea, the median number of past backers of that idea is 10 backers (i.e., the median of the variable cumulative number of backers funding idea i before day t is 10). In the six months preceding data collection, 82% of backers in our data had not funded any idea on Kickstarter. Thus, the odds of having to remember multiple cobacking relationships are relatively low. Most importantly, the median value of affiliation is zero, and the mean is 3.3. In other words, a large majority of backers in our data must process a very small amount of information to infer affiliation. Our measure of affiliation reflects a more nuanced and disaggregated conceptualization of affiliations than the number of "cobacked ideas" or the number of "common backers." Other measures are likely sparser than our measure. Subsequently, we show that our results are robust to alternate measures of affiliation.

Updates. We measure the creator's engagement using the number of creator's updates on the idea page and separately measure the level of communal content in each update. To code communal words, we created a dictionary to capture words that reflect the use of communal language. For this, we asked two graduate research assistants to read descriptions of a random sample of 100 ideas (from our data) and identify words that reflected a "communal" idea while coding each description on whether it was communal. We provided the Merriam-Webster definition of "communal" ("of or relating to a community") to the two coders along with synonyms from a thesaurus. Then, we cross-verified these words with LIWC's category for "affiliation," comprising 248 words (Pennebaker et al. 2015). Communal words that appear at least once in our corpus are member, team, group, groups, family, friends, affiliation, affiliate, relation, connection, alliance, relationship, partner, partners, partnership, link, merge, cooperate, cooperation, together, join, thanks, thank you, appreciate, our, and we. We measure backer engagement as the number of Facebook shares of the idea by backers, which we collected when the web crawler visited an idea's webpage.

Model-free evidence. To explore model-free evidence, we present summary statistics about three regimes of the distribution of the amount of daily funding achieved for Kickstarter in Table 3: (1) idea-day-specific observations when there is no funding, (2) when the daily funding is positive but does not exceed the mean level in the data (\$409.34), and (3) when the daily funding exceeds the mean level. Backer affiliation is

Table 3. Means of Backer Affiliation and Other Time-Varying Covariates at Different Levels of Daily Funding (Kickstarter).

Variable	Amount Funded $(y_{it}) = 0$	Amount Funded $0 < (y_{it}) \leq \$409.34$	Amount Funded $(y_{it}) > \$409.34$
Number of observations	17,505	11,071	3,863
Proportion of all observations	53.96%	34.13%	11.91%
Amount of funding of idea i (in \$) in day t	0	109.29	3,214.89
Backer affiliation of idea i by day t − 1 ($Affil_{it-1}$)	4.22	2.26	1.79
Cumulative number of backers funding idea i by day t − 1($CumBackers_{it-1}$)	22.65	44.23	222.89
Cumulative number of updates by creator of idea i by day t − 1 ($CumUpdates_{it-1}$)	6.21	10.54	15.76
Proportion of funding goal of idea i achieved by day t − 1 ($PropGoal_{it-1}$)	.26	.53	1.69
Proportion of funding duration of idea i completed by day t − 1 ($PropDuration_{it-1}$)	.34	.29	.27
Closeness centrality of idea i as of day t − 1	5.68×10^{-9}	4.56×10^{-9}	9.49×10^{-9}
Betweenness centrality of idea i as of day t − 1	473.99	1,178.21	5,974.58
Eigenvector centrality of idea i as of day t − 1	.001	.000	.012
Last week (1 if day t is in the last week of funding of idea i, 0 otherwise)	.10	.07	.06
Cumulative number of communal words in updates by creator of idea i by day t-1 ($CommunalUpdates_{it-1}$)	.69	1.93	199.38

highest when ideas do not receive any funding and lowest when ideas achieve the highest funding. The measure of backer affiliation for an idea on a given day is based on cobacking relationships of backers that fund the idea on that specific day with backers who funded before that day. If no backer funds on a specific day, the affiliation measure for that day is zero. The measure is not cumulative, and it does not increase over time. Thus, there is model-free evidence for the negative effect of affiliation on funding outcomes. We collected similar data from another crowdfunding platform, Indiegogo, which we use in the robustness analysis. Additional details about the Kickstarter data and summary statistics for the Indiegogo data appear in Web Appendix D. We illustrate affiliation in Figures W1–W5 and the sample's network structure and growth in Figures W6–W8 in Web Appendix E. We estimate the primary empirical model on Kickstarter data.

Empirical model. Following Burtch, Ghose, and Wattal (2013) and Zhang and Liu (2012), our primary dependent variable (y_{it}) is the monetary funding received by an idea i ($i = 1,\ldots N$) on day t ($t = 1,\ldots T_i$). As a starting point, we incorporate backer affiliation and several controls in a fixed-effects regression model as follows:

$$\begin{aligned}\log(y_{it}) = {} & \alpha_i + \alpha_t + \beta_1 \log(Affil_{it-1}) + \beta_2 \log(CumBackers_{it-1}) \\ & + \beta_3 \log(CumUpdates_{it-1}) + \beta_4 \log(y_{it-1}) \\ & + \beta_5 PropGoal_{it-1} + \beta_6 PropDuration_{it-1} \\ & + \beta_7 LastWeek_{it-1} + \beta_8 Network_{it-1} \\ & + \beta_9 \log(CommunalUpdates_{it-1}) \\ & + \beta_{10} \log(Affil_{it-1}) \times CommunalUpdates_{it-1} \\ & + \beta_{11} \log(Affil_{it-1}) \times FBShares_i + e_{it}.\end{aligned} \tag{1}$$

To account for nonnegativity, we log-transform all variables that are not proportions. For variables that can take zero values, we take the logarithm of the variable added to .001. Replacing this constant with other constants does not affect our results. Estimating the model without taking logarithms of any variable gave us consistent results.

To control idea-specific confounding factors such as inherent differences in idea quality, the novelty of idea description, creator expertise, and so on, we employ idea-specific fixed effects α_i, a vector of 2,021 elements for the Kickstarter data set. We incorporate fixed effects for each day in the idea's funding window to control temporal patterns in funding and changes in the Kickstarter environment over time. These are denoted by the vector α_t. Error terms are assumed normally distributed and clustered at the idea level.

Our key independent variable is $Affil_{it-1}$. This is the number of cobacking relationships between those backers who fund idea i on day t − 1 and all backers who have funded this idea before day t − 1. Subsequently, we report robustness checks to alternate measures of backer affiliation. Although our fixed-effects specification controls for confounds at the idea level and the day level, we need to control idea-specific factors that are time varying. Chief among these is the amount of funding received by the focal idea on day t − 1 (Burtch, Ghose, and Wattal 2013), enabling us to control those time-varying idea-specific unobservables, which may be serially correlated (e.g., word of mouth about the idea) and to attenuate serial correlation among the residuals. This also accounts for the alternate explanation that affiliation on day t − 1 affects funding on day t − 1, but not on day t. By incorporating the lagged measure of funding, we can account for all factors that affect funding until the day t − 1.

We next discuss other time-varying idea-specific controls. First, the number of affiliations among backers is correlated

Table 4. Pairwise Correlation Coefficients of All Variables (Kickstarter).

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Amount of funding of (in $) in t	1										
2. Backer affiliation i by t − 1	**−.07**	1									
3. Cum. number of backers funding by t − 1	**.13**	**.14**	1								
4. Cum. number of updates by creator i by t − 1	**.13**	**.15**	**.18**	1							
5. Amount of funding (in $) in t − 1	**.49**	**−.11**	**.17**	**.15**	1						
6. Proportion of funding goal achieved by t − 1	**.15**	.00	**.12**	**.20**	**.19**	1					
7. Proportion of funding duration completed by t − 1	**−.11**	**.37**	**.05**	**.30**	**−.19**	**.05**	1				
8. Closeness centrality as of t − 1	.01	**−.07**	−.00	**−.04**	**.14**	**−.01**	**−.12**	1			
9. Betweenness centrality i as of t − 1	**.09**	**.37**	**.23**	**.29**	.07	**.07**	**.32**	**−.07**	1		
10. Eigenvector centrality as of t − 1	**.05**	**.04**	**.33**	**.09**	**.07**	**.04**	.00	**.07**	.09	1	
11. Last week (1 if day t is in the last week of funding)	**−.05**	**.14**	**.02**	**.15**	**−.05**	**.05**	**.61**	**.03**	.01	.00	1
12. Cum. no. of communal words in updates by t − 1	**.02**	**.02**	**.26**	.01	**.03**	.00	−.00	.01	.00	**.09**	−.00

Notes: We take logarithms of all variables, which are not proportions. For variables that can take zero values, we take the logarithm of the variable added to .001. All variables pertain to the focal idea. Coefficients with $p < .05$ are in boldface.

with the number of backers. There can be no backer affiliations without backers; more backers could result in more possibilities for affiliation. To control for the possibility that the number of backers drives the effect of affiliation on funding, we include $CumBackers_{it-1}$, the cumulative number of backers funding idea i by day t − 1, as a control variable. Also, to the extent that ideas with more backers attract more funding (Zhang and Liu 2012), this serves as a measure for herding behavior. Second, creators communicate with backers via updates, a means to elevate idea visibility and signal effort (Dai and Zhang 2019). To understand how creator actions might drive funding, we include $CumUpdates_{it-1}$, the cumulative number of updates by the creator of the idea i by day t − 1. In addition, $CommunalUpdates_{it-1}$ is the number of communal words contained in the updates.

Third, the funding window of an idea influences its funding outcomes. Ideas receive more funding in the later stages of the funding window as the funding deadline nears (e.g., Dai and Zhang 2019; Kuppuswamy and Bayus 2017). To account for this, we include the duration of the funding window completed for the idea ($PropDuration_{it-1}$) as a proportion of the total funding window (typically 30 days). Furthermore, ideas receive greater funding as they get closer to meeting their funding goals (Dai and Zhang 2019). Although daily fixed effects account for temporal variations in funding, they might not capture the effect of proximity to the funding goal. Therefore, we include $PropGoal_{it-1}$, the proportion of the funding goal of the idea that has been achieved until day t − 1, and $LastWeek_{it-1}$, a dummy variable for whether the observation belongs to the last week of the funding window.

Finally, structural measures of network centrality might affect the outcome. Because these measures capture the extent of social capital that accrues to ideas due to being associated with certain backers, we want to control for the effects of these measures. We compute and include three of the most widely used network measures in marketing (e.g., Mallapragada, Grewal, and Lilien 2012; Ransbotham, Kane, and Lurie 2012; Swaminathan and Moorman 2009), ($Network_{it-1}$): closeness centrality, betweenness centrality, and eigenvector centrality of idea i on day t. Closeness centrality in our context is how close the focal idea is from all the backers (connected and not connected) in the network, betweenness centrality is the extent to which the focal idea lies on the common paths between all pairs of backers in the network, and eigenvector centrality is the extent to which the focal idea's backers are prolific in backing other ideas. We computed both bipartite and single-mode network variants of each of these measures.[3] Given the high correlation across the bipartite and single-mode versions of each measure, we included in the model the version of each measure that leads to a more significant improvement in R^2. As shown in the correlation matrix of all variables (Table 4), these variables are not highly correlated with our measure of affiliation, suggesting that affiliation captures the network's unique structural properties based on counts of overlaps. To assess interaction effects, we interact affiliation with $CommunalUpdates^4_{it-1}$ and with the number of Facebook shares of the idea by backers ($FBShares_i$).

We use lags of all covariates because information about the focal day is not updated in real time and is unavailable until the following day.[5] We present the correlation matrix of all

[3] Clustering coefficient, a related network measure, deserves mention. A node's clustering coefficient is the proportion of nodes in its neighborhood that are connected to each other (Watts 1999). In our context, the clustering coefficient of an idea would be the proportion of existing backers that have other cobacking relationships with each other.

[4] We transformed this variable, such that the transformed variable is 0 if $Affil_{it-1} \times CommunalUpdates_{it-1} = 0$ and the transformed variable is 1 if $Affil_{it-1} \times CommunalUpdates_{it-1} > 0$. Because $Affil_{it-1} \times CommunalUpdates_{it-1} = 0$ for 93.3% of all observations, this transformation does not significantly change the original variable but offers the advantage of reduced multicollinearity. The variance inflation factor of the transformed variable is 1.9.

[5] Our results are robust to the inclusion of four additional controls: (1) a dummy for whether the funding goal has been met; (2) the number of backers of the focal idea on the focal day; (3) "backer propensity," a measure of how likely backers are to fund the project; and (4) "backer longevity," a measure of how long backers have been active on the platform.

variables in Table 4; most correlations are less than .3, allaying multicollinearity's ill effects.

Empirical strategy. We first discuss how our work is different from the peer effects literature and then explain our identification strategy. The prototypical problem in the marketing literature on the identification of peer effects (e.g., Nair, Manchanda, and Bhatia 2010) is to estimate the likelihood of agent A adopting a product (e.g., buying an online game) under the knowledge that agent B (a self-identified "friend" or influencer) has already adopted that same product. The herding literature has conclusively documented positive peer effects across various consumer contexts (e.g., Sunder, Kim, and Yorkston 2019; Zhang and Liu 2012). If there are positive effects due to the size of the crowd or the number of peers, that would be equivalent to herding, not our study's primary focus. In other words, our main objective is not to estimate how backer A will fund the focal idea if another backer B has previously funded it. We account for herding in our model by incorporating the prior number of backers of the focal idea as a control. Instead, our objective is to study the effect of affiliation, which is formed when two backers back an idea that is not the focal idea. Affiliation arises in collaborative contexts (e.g., board interlocks, product development teams) rather than common product purchases. We note that this is a key difference of our article from other contexts. In addition, our interest is less in modeling agent behavior (e.g., an individual's rating of a product in Sunder, Kim, and Yorkston [2019]) than in modeling product success (i.e., funding success of an idea). We next address three main issues that could confound identifying the causal effect of affiliation on the focal idea's funding.

Correlated unobservables. Idea-specific characteristics that are not observable to the researcher could be correlated with our affiliation measure and affect the focal idea's funding. Perhaps highly affiliated backers are attracted to ideas with high (or low) unobserved quality. The inability to control for quality dimensions might induce an upward (or downward) bias in our estimate of the effect of affiliation. Following Nair, Manchanda, and Bhatia (2010) and Sunder, Kim, and Yorkston (2019), we incorporate idea-specific fixed effects. These effectively control for all idea-specific factors that might be correlated with affiliation. Next, there could be time-varying factors across the funding window that might be correlated with affiliation and funding. For example, affiliation and funding are both likely to be low in the first few days of funding. We control for all day-specific trends by incorporating day fixed effects. Finally, the presence of idea-specific time-varying factors cannot be ruled out. We control for funding received by the focal idea on day $t-1$. As mentioned previously, this approach enables us to control those time-varying idea-specific unobservables, which may be serially correlated, and to attenuate serial correlation among the residuals.

Simultaneity. In the context of peer influence, simultaneity implies that not only can the influencer influence the focal individual but the focal individual could also affect the influencer's actions, leading to an upward bias in the estimate of peer effects. In our context, affiliations formed on a focal day may affect the focal idea's funding. Simultaneously, the focal idea's funding on a focal day also affects affiliation formation on that day. Following recent literature (e.g., Park et al. 2018), we use the lagged measures of affiliation in the model. While affiliation before the focal day can affect funding on the focal day, the reverse is not possible.

Endogenous group formation (or homophily). Backers with similar preferences may be more likely to behave similarly. In such a scenario, the effect of prior affiliation on subsequent funding of the focal idea might manifest these common preferences. The literature on consumer peer effects has used consumer-specific fixed effects to deal with this. However, crowdfunding is different from consumer contexts in that while consumers buy (and evaluate) several products, backers typically fund very few ideas on a platform.

Moreover, unlike crowdfunding, consumer contexts generally focus on the individual more than collective action (Simpson et al. 2021). So, backer-specific fixed effects are econometrically infeasible to estimate for both the researcher and the platform. Instead, we first include the cumulative number of backers and several other network measures as controls. Next, we note that controlling for lagged funding of the idea also controls backer characteristics that have affected funding before the focal day.

Finally, we include an instrument for affiliation. If our measure of affiliation is correlated with the error term in Equation 1, its coefficient could be biased. In our primary analysis, we use an observed instrument to estimate a two-stage least-squares instrumental variable regression model. As Rossi (2014, p. 4) mentions, the ideal solution for endogeneity is to conduct an experiment where the endogenous variable is uncorrelated with the construction's dependent variable. Therefore, we ran controlled experiments, which we explain subsequently, where participants were randomly assigned to different affiliation levels, creating exogenous variation.

For the primary instrumental variable approach, we follow recent research (e.g., Germann, Ebbes, and Grewal 2015; Sridhar et al. 2016) that uses instruments based on agent behavior in categories (or firms) different from the focal category (or a firm). Following this approach, we use the mean (across ideas) of affiliations on day $t-1$ of all ideas in our Kickstarter data, which are in a category different from that of the focal idea as the primary instrument for Affil_{it-1} in Kickstarter. For example, for an observation about an idea on movies on December 22, this instrument is the mean of affiliations on December 22 of all ideas in our data that are not in the movies category. This instrument is correlated with Affil_{it-1} (correlation = .16).

Conceptually, this instrument is appealing because of the interdependencies across different parts of the global affiliation network on Kickstarter (i.e., the affiliation network across all ideas seeking funding concurrently), thus satisfying the relevance criterion. However, because most backers only back one idea (i.e., affiliation is sparse), the mean affiliation across ideas in other categories is very unlikely to be related to the unobserved component of the focal idea's funding outcome in Equation 1 providing the basis for identification. Further, a category-level measure of affiliation should remain unaffected by idea-level factors, especially if the idea is from a different category. A category-level measure should not correlate strongly with idea-day-level idiosyncratic shocks from another category, thus meeting the exclusion criterion. The first-stage equation is specified as

$$\begin{aligned}\log(\mathrm{Affil}_{it-1}) = \lambda_0 &+ \lambda_1 \mathrm{IV}_{it-1} + \lambda_2 \log(\mathrm{CumBackers}_{it-1}) \\ &+ \lambda_3 \log(\mathrm{CumUpdates}_{it-1}) + \lambda_4 \log(y_{it-1}) \\ &+ \lambda_5 \mathrm{PropGoal}_{it-1} + \lambda_6 \mathrm{PropDuration}_{it-1} \\ &+ \lambda_7 \mathrm{LastWeek}_{it-1} + \lambda_8 \mathrm{Network}_{it-1} \\ &+ \lambda_9 \log(\mathrm{CommunalUpdates}_{it-1}) + \delta_{it-1}.\end{aligned} \tag{2}$$

The R^2 for the first stage regression without the instrument (i.e., assuming that $\lambda_1 = 0$) is .365 and with the instrument is .385, showing that the instrument's addition improves the in-sample model fit. The estimate of λ_1 is .42 ($p < .01$). The corresponding F-statistic for the F-test of excluded instruments is 879.83, far exceeding the threshold value of 10 (Stock, Wright, and Yogo 2002, p. 522). The large value of the Anderson–Rubin statistic ($F(1, 28{,}300) = 298.41$) rejects the null hypothesis that the instrument is weak. We show in robustness analyses that the estimates are consistent across the use of alternative instruments. We also instrument for the interaction of affiliation and the number of communal words contained in the updates ($\mathrm{CommunalUpdates}_{it-1}$). Following Papies, Ebbes, and Van Heerde (2017), the instrument for this interaction variable is the interaction of the instrument for affiliation and $\mathrm{CommunalUpdates}_{it-1}$. We do not instrument for the interaction of affiliation and the number of Facebook shares, because the Durbin–Wu–Hausman test of the hypothesis that this regressor is exogenous could not be rejected ($\chi^2 = .055$, $p > .1$). Furthermore, the sharing activity of a specific idea on a social media platform other than Kickstarter is conceptually independent of its funding outcome on Kickstarter.

Results. First, we present the parameter estimates of the instrumental variable regression models estimated on the Kickstarter data and then discuss robustness checks. We present estimates of five models, with and without instruments, and the sequential addition of interactions in Table 5. M1–M4 do not have interaction effects, and while M1 ignores endogeneity, M2, M3, and M4 correct for it and show that the results are robust to different instruments. The results from the full model specified in Equation 1 are reported in M5, which we discuss next.

Full model results. We find that affiliation among backers has a consistent negative effect on the funding of ideas on Kickstarter ($\beta = -.87$, $p < .01$). This effect persists despite the inclusion of idea-specific fixed effects, daily fixed effects, controlling for lagged funding, and the prior number of backers of the idea. We corroborate extant findings on herding (e.g., Zhang and Liu 2012) and additionally show that affiliation plays a key role and that its effect is negative.

Concerning the moderators, the creator's engagement measured as using communal words in updates further strengthens the negative effect of affiliation, perhaps because of a heightened licensing effect ($\beta = -7.68$, $p < .01$). For backer engagement, we find the negative effect of affiliation is stronger as backer engagement, measured as the number of Facebook shares of the idea by backers, increases ($\beta = -.006$, $p < .01$). One explanation of this is that while individuals share on Facebook for various motives, the primary motivation is prosocial, and others seeing the shares likely see them as such, strengthening the vicarious moral licensing effect (Kim and Yang 2017).

Concerning control variables, the greater the number of backers of an idea before the focal day, a measure of herding, the more funding the idea will attract on the focal day ($\beta = 2.02$, $p < .01$). This indicates that the total number of backers for an idea may act as a signal of its quality or potential worthiness, a finding that is consistent with prior research (e.g., Lin, Prabhala, and Viswanathan 2013). The current research replicates this effect and demonstrates that social structure influences behavior beyond the herding effect. Moreover, this theory supports our contention that affiliation, measured by cobacking, drives the negative effect, not herding. We also find that the total number of updates posted by the creator has a negative effect on crowdfunding success ($\beta = -.05$, $p < .10$), although this effect is not significant across all model specifications. The effect of the proportion of the funding goal which was achieved on the previous day is negative ($\beta = -.17$, $p < .05$), perhaps suggesting a preference to fund underfunded ideas. For network centrality measures, we find that betweenness ($\beta = -.02$, $p < .05$) and eigenvector centrality ($\beta = -4.40$, $p < .05$) have a negative effect on funding. The negative effects of these second-order network measures, compared with the positive effect of number of backers (proxy for first-order network effect), highlight the complexity in flow of information on the network and are consistent with findings from prior studies (e.g., Mallapragada, Grewal, and Lilien 2012). This is perhaps because these measures indicate the backers' ability to identify and fund salient opportunities, or access to information from their overall networks about idea quality based on indirect ties across the whole network, not just direct ties. Thus, the effects also highlight the importance of distinguishing direct and indirect aspects of how networks operate in community contexts.

To ensure that outliers are not driving our results, we estimate the main model (M5) after dropping the top 10th percentile of observations (which have affiliation values greater than 7), yielding a significant and negative estimate of the affiliation coefficient ($\beta = -.87$, $p < .01$). We find a similar negative effect in models estimated on various subsets of the data. To investigate if specific categories of ideas drive our results, we estimate the model separately for each category's ideas. We find a negative effect of affiliation for 11 out of 12 categories,

Table 5. Coefficient Estimates of the Fixed-Effects Regression Model of Daily Funding of Ideas on Kickstarter.

Variable	M1	M2	M3	M4	M5 (Final Model)
Backer affiliation of idea i by day t − 1 ($Affil_{it-1}$)	−.04***	−.86***	−1.88***	−.80***	−.87***
	(.01)	(.06)	(.41)	(.06)	(.06)
Cumulative number of backers funding idea i by day t − 1 ($CumBackers_{it-1}$)	.15**	1.92***	4.13***	1.79***	2.02***
	(.06)	(.15)	(.90)	(.15)	(.16)
Cumulative number of updates by creator of idea i by day t − 1 ($CumUpdates_{it-1}$)	−.05**	−.06**	−.07*	−.06**	−.05*
	(.02)	(.03)	(.04)	(.03)	(.03)
Amount of funding of idea i (in $) on day t − 1	−.03	.01	.07**	.01	.01
	(.02)	(.02)	(.03)	(.02)	(.02)
Proportion of funding goal of idea i achieved by day t − 1	−.09	−.23***	−.39**	−.22**	−.17**
	(.06)	(.07)	(.10)	(.07)	(.07)
Proportion of funding duration of idea i completed by day t − 1	−.27	1.12	2.84*	1.02	.63
	(.99)	(1.10)	(1.65)	(1.09)	(1.10)
Closeness centrality of idea i as of day t − 1	2.54	2.43	8.46	1.99	2.71
	(3.12)	(3.54)	(5.30)	(3.48)	(3.54)
Betweenness centrality of idea i as of day t − 1	−.02**	−.02**	−.03*	−.02**	−.02*
	(.01)	(.01)	(.02)	(.01)	(.01)
Eigenvector centrality of idea i as of day t − 1	−.74	−4.39*	−8.95*	−4.13*	−4.40*
	(.82)	(2.33)	(4.66)	(2.21)	(2.67)
Last week (1 if day t is in the last week of funding of idea i, 0 otherwise)	.25	.13	.03	.14	.09
	(.21)	(.24)	(.35)	(.24)	(.25)
Cumulative number of communal words in updates by creator of idea i by day t − 1 ($CommunalUpdates_{it-1}$)	−.04	−.02	−.01	−.02	−.29*
	(.03)	(.03)	(.04)	(.03)	(.15)
Interactions of Backer Affiliations					
$Affil_{it-1}$ × $CommunalUpdates_{it-1}$					−7.68**
					(3.80)
$Affil_{it-1}$ × Number of Facebook shares of idea i					−.006***
					(.001)
Fixed effects for each idea i	Yes	Yes	Yes	Yes	Yes
Fixed effects for each day t	Yes	Yes	Yes	Yes	Yes
Instrument for $Affil_{it-1}$	No	Yes	Constra	Other	Yes

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: "Constra" refers to Burt's (1992) measure of constraint of the focal idea. "Other" instrument refers to the instrument constructed from Indiegogo data.

with the most negative effect of affiliation in the ideas from the photography and technology categories. Our estimate of affiliation's effect is negative but not statistically significant for the "dance" category, which accounts for just 21 out of 2,021 ideas in our data.

Robustness analyses. We conducted several robustness analyses. First, we estimated the model on Indiegogo data; the results are quite consistent (see Web Appendix F). Second, we estimated the model on Kickstarter data using three alternative sets of instruments: discrete latent instrumental variables, an instrument constructed using affiliation from another platform, and a network-based instrument (see Web Appendix G). Third, we estimated probit, logit, and Tobit models of funding success and checked the robustness of our results to two alternative measures of affiliation (Web Appendix H). All analyses show that our results are robust. Next, we report three experiments in which we probe the effect of affiliation, the underlying process, and a moderating factor to further validate our empirical model.

Collection and Analysis of Experimental Data

In the first experiment, we demonstrate the negative effect of affiliation in a controlled experimental setting. In the second experiment, we validate vicarious moral licensing as an underlying mechanism and rule out uniqueness as one potential alternative explanation. In the third experiment, we show how the idea's description might moderate the effect of affiliation.

Experiment 1. We conducted Experiment 1 on MTurk with 200 North American residents[6] ($M_{age} = 35.26$ years; 49.8% women; 42.6% have previously funded a crowdfunding idea). We presented participants with two ideas seeking funding (both real

[6] Because this study involved real pay, we restricted participants to exclude those who had completed over 1,500 studies, as these "professional" MTurkers may behave in significantly different ways, particularly when monetary bonuses are included (Wessling, Huber, and Netzer 2017).

ideas from Kickstarter; see Web Appendix I). First, participants saw a screenshot of a website created by a graphic designer to look like an idea page on a real crowdfunding platform (e.g., Burtch, Ghose, and Wattal 2013; Younkin and Kuppuswamy 2017).

Consistent with prior research, participants were given money beyond study payment, creating an incentive-compatible dependent measure (Goenka and Van Osselaer 2019; Morewedge, Zhu, and Buechel 2019). Participants were told, "As part of this study, you will receive a $2 bonus. You can use some or all of this money to fund this project." They were then asked how much they would give toward the idea on a nine-point scale with dollar amounts in $.25 intervals, ranging from $0 to $2.00. If participants chose "$0" and opted to keep the full bonus, they were then forwarded to the end of the survey and were paid the original MTurk fee as well as the $2 bonus. If participants used any of their bonus to fund the first idea, they were included in our primary analyses. Ninety-three participants opted not to fund the first idea, leaving us with 107 participants. Four participants were removed who indicated that they had a child affected by autism, the focus of one of the two ideas, and were inclined toward funding but would opt to put the money toward helping their child. All participants completed the dependent measures. Two participants were removed for spending less than a second on the manipulation, leaving us with 101 participants. Participants then saw a screenshot of a second website designed to look like an idea on a crowdfunding platform (for details, see Web Appendix I).

The screenshot included idea information and a list of recent backers shown on the screen's right side. Participants in the high-affiliation condition saw a high overlap in the number of backers across the two ideas. Participants in the control-affiliation condition saw the same number of backers, but the names on the two lists did not overlap. A manipulation check confirmed the effectiveness of the manipulation. All participants who funded the first idea were told that they would receive an additional $2 bonus to keep or use to fund the second idea. Their decision on a nine-point scale ranging from $0 to $2.00 in $.25 intervals served as the outcome. At the end of the study, participants were given the money that they chose to keep as a bonus, and the remainder (i.e., what they chose to fund each of the ideas) was put toward each crowdfunding idea. Finally, participants responded to a set of demographic measures (e.g., age, gender, whether they had previously funded an idea on a crowdfunding platform). A one-way analysis of variance showed a significant effect of affiliation on the funding of the second idea ($F(1, 99) = 4.05$, $p < .05$). As we expected, those in the high-affiliation condition funded less than those in the control-affiliation condition ($M_{high} = 4.27$, $SD = 2.27$ vs. $M_{control} = 5.27$, $SD = 2.70$). Of the $2 bonus, those in the high-affiliation condition chose to fund $.82 toward the focal idea, while those in the control-affiliation condition chose to fund $1.07, on average.

The first experiment confirmed the negative effect of affiliation in the lab setting, validating our primary empirical finding that affiliation negatively affects crowdfunding success.

Experiment 2. In the second experiment, we measured two potential mediators in an attempt to document "a" mediating process (i.e., the mediating process given our stimuli and procedures) as opposed to "the" mediating process (i.e., a single mediating process that is operative across all crowdfunding contexts; e.g., Buechel and Janiszewski 2013). We propose vicarious moral licensing as a mechanism for the negative impact of affiliation on funding and test need for uniqueness as an alternative mechanism (Tian et al. 2001).

We conducted the study on MTurk with 228 North American residents ($M_{age} = 39.57$ years; 54.4% women; 38.2% had previously funded an idea on an online crowdfunding platform). All participants spent adequate time on the manipulation. Three participants did not complete the dependent measures, resulting in an effective sample of 225 participants. Participants were told to imagine that they had $50 and were asked to choose one idea to fund from a set of four real ideas seeking funding on Kickstarter and across categories (e.g., technology, nonprofits, arts/film); details appear in Web Appendix I. After this decision, they read about a second idea that they were told is seeking funding. Those in the high-affiliation condition were told that many of the backers who funded the first idea they chose also funded the focal idea. Those in the control affiliation condition were provided no information about other backers' funding decisions. A pretest confirmed the effectiveness of the manipulation (see Web Appendix I). Next, participants responded to two items to capture vicarious moral licensing ("Based on the funding behavior of cobackers, I do not feel the need to fund [focal idea]" and "Based on the funding behavior of cobackers, I do not feel obligated to fund [focal idea]"; $M = 4.10$, $SD = 1.48$; $r = .72$) and two items to capture uniqueness ("If I funded [focal idea], my decision to fund would say a lot about me as a unique individual" and "If I funded [focal idea], it would help me stand out from the crowd"; $M = 3.68$, $SD = 1.45$; $r = .81$).

Next, we asked participants how much money they would pledge toward funding the subsequent focal idea (range: $0–$5,000, the total needed to hit the focal idea's funding goal). Consistent with prior research and our empirical model, we log-transformed funding (Matthews, Gheorghiu, and Callan 2016). Finally, participants completed demographic questions.

As expected, we found a negative effect of affiliation on funding ($F(1, 223) = 4.29$, $p < .04$) such that those in the high-affiliation condition reported a lower funding amount than those in the control condition ($M_{high} = 3.17$, $SD = 2.49$ vs. $M_{control} = 3.82$, $SD = 2.24$) or in raw numbers ($M_{high} = \$256.96$, $SD = \$674.40$ vs. $M_{control} = \$339.88$, $SD = \$875.90$). A one-way analysis of variance showed a significant effect of affiliation on the licensing measure ($F(1, 223) = 3.89$, $p = .05$). As we expected, those in the high-affiliation condition agreed more with the licensing measure, indicating less need to fund than those in the control condition ($M_{high} = 4.29$, $SD = 1.57$ vs. $M_{control} = 3.90$, $SD = 1.37$). However, there was no significant effect of affiliation on uniqueness ($M_{high} = 3.56$, $SD = 1.52$ vs. $M_{control} = 3.80$, $SD = 1.36$; $F(1, 223) = 1.53$, $p = .22$). We then assessed the indirect effects of the two mediators on funding. The results indicate that licensing was a significant mediator (95% confidence interval does not include 0: [−.4423, −.0003]), but uniqueness was not (95% confidence interval: [−.5479, .1142]).

In this experiment, we replicated the negative effect of affiliation and uncovered vicarious moral licensing as an underlying mechanism. Although we did not find an effect of affiliation on uniqueness in this study, we note that uniqueness may operate more strongly for some ideas and some individuals, providing an interesting avenue for future research on crowdfunding (Tian et al. 2001).

Experiment 3. In Experiment 3, we explored the role of a moderator: how the creator describes the idea. We theorized that the negative effect of affiliation occurs in a crowdfunding context, at least partly due to its communal nature and how the ideas are presented to potential backers. We conducted the third experiment on MTurk with 206 North American residents (M_{age} = 38.81 years; 46.1% women; 42.2% have previously funded an idea on an online crowdfunding platform). All participants completed the dependent measures. Three participants who spent less than one second reading the manipulation were removed, resulting in N = 203. We manipulated two factors between participants: (1) affiliation (high vs. control) and (2) idea description (more vs. less communal).

As in Experiment 2, participants read about an idea currently seeking funding on Kickstarter and were told to imagine that they had funded this idea (see Web Appendix I). We used the same manipulation of affiliation as in Experiment 2. Those in the high-affiliation condition were told that many backers who funded the first idea they chose also funded the focal idea. Those in the control-affiliation condition were not provided any information about other backers' funding decisions. Participants then read about diveLIVE, a technology that allows divers to talk underwater while streaming live video to the internet. diveLIVE, the focal idea, was described as more or less communal with small changes (e.g., "Let's learn about the oceans" vs. "This product uses technology to take videos of the oceans").

Next, participants indicated how much money they would pledge toward diveLIVE, the focal idea (range: $0–$20,000, the total needed to hit the focal idea's funding goal). Consistent with prior research, our empirical model, and Experiment 2, we log-transformed funding (Matthews, Gheorghiu, and Callan 2016) for analysis but provide results in raw numbers for ease of interpretation. Finally, participants completed demographic questions.

We found evidence for a main effect of idea description ($F(1, 199) = 13.86$, $p < .01$) consistent with prior research, which finds that ideas described as more communal tend to be more successful than those described as an investment opportunity (Allison et al. 2015). More importantly, we found an interaction between the two manipulated factors ($F(1, 199) = 5.84$, $p < .02$). As we expected, when the idea was described as more communal, those in the high-affiliation condition reported lower funding than those in the control-affiliation condition (M_{high} = $2,155.32, SD = $3,998.08 vs. $M_{control}$ = $4,073.04, SD = $5,316.08; $t(199) = 2.09$, $p < .04$). When the idea was described as less communal, there was no effect of affiliation on funding (M_{high} = $2,572.33, SD = $4,933.01 vs. $M_{control}$ = $1,868.68, SD = $4,039.03; $t(199) = -1.34$, $p = .18$; see Figure W9 in Web Appendix I). The third experiment established that the negative effect of affiliation is stronger when creator's use more communal words in the description of the idea.

Validating Moderation with Observational Data

As discussed previously, we find a negative moderating effect of the number of communal words in updates posted by creators. To validate the third experiment with converging evidence, we returned to our secondary data to examine how the number of communal words in the idea description influenced the relationship between affiliation and funding behavior across thousands of crowdfunding ideas (e.g., Netzer, Lemaire, and Herzenstein 2019). This would establish how the use of communal words in creator's updates as well as in the idea's description would influence the effect of backer affiliation and highlight the importance of the communal mechanism. We used the same text dictionary that we created for coding communal words in updates and coded the description of every idea in our sample. The median number of communal words in an idea description is 3 (M = 6.1). We then created two subsets of our data based on a median split of the number of communal words used in describing the idea. We estimated the model separately on each subset and find that the coefficient of affiliation is less negative for ideas described using three or fewer communal words (M = −.92, SE = .09) than for ideas described using four or more communal words (M = −1.25, SE = .15). Replacing the number of communal words in this analysis with the ratio of the number of communal words to the total number of words does not affect this result, nor does splitting the data on the basis of the average number of communal words instead of the median. Finally, the effect of affiliation is less negative for ideas with no communal words than for ideas with at least one communal word. This provides real-world evidence for the role of idea description on the relationship between affiliation and funding behavior, validating our theory and experimental evidence.

In summary, these findings further support our reasoning that the negative effect of affiliation is driven, at least in part, by the communal nature of crowdfunding and the prosocial mindset that it prompts (Simpson et al. 2021). When an idea is described as more communal, these prosocial goals are exacerbated, leading potential backers to feel that they do not need to fund the idea because these affiliated others are funding it (e.g., Meijers et al. 2019). However, when an idea is described as less communal, this effect is mitigated. Next, we discuss our results and develop implications for theory and practice.

Discussion

We establish a negative effect of affiliation on the crowdfunding success of ideas using a large empirical study and then validating the effect through experiments. We provide preliminary insights into the role of vicarious moral licensing as the underlying mechanism for this effect and investigate the moderating role of creator and backer engagement. The licensing effect and its role in reducing backers' perceived obligation to fund ideas could make backers less likely to fund or fund with less money if they opt to fund, both of which could explain the negative effect at the idea level. We begin with a focus on the novel contribution of our finding concerning affiliation, discuss the economic implications of our results, and identify the primary contributions of our research and how it paves the way for future research.

The negative effect of affiliation among backers in crowdfunding is distinct from and in addition to the positive effect of herding due to the crowd's size shown in prior research (e.g., Zhang and Liu 2012). We establish an inherent tension between the positive effect of crowd size and the negative effect of backer affiliation in crowdfunding. Thus, we show that, in addition to relying on crowd size, backers make inferences based on the behavior of affiliated others in a crowdfunding context. A 10% daily increase in number of backers leads to an additional 20.2% in funding or an increase of US$83/day (i.e., the herding effect). In contrast, a 10% daily increase in backer affiliation leads to an 8.7% decrease in funding or a decrease of US$36/day, offsetting the increase due to number of backers by 43%. Our results concerning affiliation are both statistically and economically meaningful and highlight the need to recognize the tension between increasing the number of backers and limiting the ill effects of affiliation.

Interestingly, Kickstarter stopped disclosing the prior backers' list on an idea's page as of the time of writing this article. This policy change is consistent with our results. If backer identities remain unknown, potential backers cannot infer affiliation, and therefore ideas cannot be negatively impacted by backer affiliation. Other crowdfunding platforms should reevaluate disclosure policies about past backers of an idea or perhaps reconsider whom they show at the top of their backer lists.

So how might creators mitigate the negative effects of affiliation? The moderation effects from our results provide actionable insights for creators seeking crowdfunding from potential backers and considering what platforms to pursue. Our results concerning the interaction between affiliation and creator engagement show that creators can subdue the negative effects of affiliation by carefully crafting the idea description and updates, avoiding communal language.

Further, while it appears that encouraging backers to share the idea on social media might be counterproductive because it strengthens affiliation's negative effect, the impact is small and should not be a major concern. The change in the marginal effect of affiliation as sharing by backers increases is small, indicating that change in backers' engagement, while statistically significant, does not have a meaningful effect on crowdfunding. Doubling the number of Facebook shares from its mean of 79 to 148 strengthens the negative effect of affiliation by .42% and translates to a decline of 1.72 USD/day.

We developed recommendations for creators and examples of best practices from our data set (see Table 6). For example, creators should focus on the idea's inherent purpose and objective value in its description and avoid using too much communal language (e.g., cooperate, partner, support) in the idea description and updates. Overall, we recommend that platforms educate creators on how best to structure communication with backers and guide creators in meeting their goals. Backers could perhaps learn to interpret such updates better and use the information provided by the backer to qualify what they infer from the community.

Our results about the mechanism provide insights on how platforms and creators should engage with backers. Research has shown that licensing is a nonconscious effect and can be mitigated by making individuals aware of their behavior (Khan and Dhar 2006). Particularly in this type of vicarious moral licensing, highlighting individuals' uniqueness and independent identity may also mitigate the negative effect of affiliation on funding (Kouchaki 2011; Meijers et al. 2019; Newman and Brucks 2018). If creators expect high overlap among backers, they could describe their ideas using less communal language, thereby lowering the licensing effect. Our results suggest that vicarious licensing might overwhelm other relevant idea information, potentially leading to suboptimal backer decisions. In line with our findings, backers might, in some cases, pay more attention to signals from affiliated others rather than from the whole crowd.

For crowdfunding platforms, our findings provide a rationale for why there might be room for new crowdfunding platforms to thrive and grow. Although several crowdfunding platforms have flourished in the past decade, Kickstarter, Indiegogo, and GoFundMe have arguably dominated the market. Other once-popular platforms, such as Sellaband and PledgeMusic, have failed. Large platforms with millions of backers might pose high entry barriers to new entrants. However, our findings point to one source of competitive advantage for newer platforms: negative affiliation effects are more likely to occur in well-established platforms with large backer communities. Strategically building diverse and unaffiliated communities of backers might confer a competitive advantage to new platforms. Our results show that this can be achieved by expanding the number of categories of ideas, as affiliation's negative effect may be mitigated as backers of ideas across different categories may be less likely to coback ideas. The failure of category-specific platforms such as Sellaband (music), and the relative success of platforms hosting diverse ideas, such as Kickstarter, provides support for this reasoning. Second, platforms allocating marketing resources across existing and new backers (e.g., allocating social media spending across established markets such as Los Angeles and new markets such as Lima) could perhaps view our results as a reason to divert resources away from backer-dense markets. Third, platforms that provide backer information may also want to use algorithms that promote unaffiliated (vs. affiliated) backers, for example, by highlighting first-time backers. Finally, drawing on our results about creator engagement, we recommend that platforms educate creators on how to design better backer communication.

Insights from our study are relevant to other types of crowdsourcing platforms as well. For example, participants on

Table 6. Actionable Outcomes for Managers Recommendations for Idea Descriptions and Updates.

Finding	Recommendations for Creators	Examples from Kickstarter Data
Interaction between affiliation and communal words in idea description	Focus on the idea's inherent purpose as opposed to a focus on community.	**The Drone Pocket** Idea Description: "The world's first multicopter that's powerful enough to carry a high-quality action camera and folds up smaller than a 7 in tablet." Key technology features outlined prominently on idea's home page. *Total Amount Raised*: $929,212 **Pegasus Touch Laser SLA 3D Printer** Idea page includes recent press articles with links that highlight idea's features *Total Amount Raised*: $819,535
	Use noncommunal words (e.g., "you" vs. "we") in idea description.	**The Floyd Leg** "The Floyd Leg gives *you* the framework to take ownership of *your* furniture by allowing *you* to create a table from any flat surface" (emphasis added) *Total Amount Raised*: $256,273
	Avoid thanking backers too much in idea description, as it can make the project appear needy.	"First off, I want to say thanks for checking out of project. Every single person that takes the time to look at our project means the world to us."
	Do not describe idea with overemphasis on communal language (e.g., "support," "team").	"As we approach Thanksgiving, I continue to be thankful for the patience and support that the unsung backers have shown with our team."
Interaction between affiliation and communal words in updates	Do not show too much appreciation via updates for funding as it is progressing.	"Thanks to all of you who pledged for this campaign. We really appreciate your continued support."
	Minimize communal language (e.g., partner) in updates.	"Your first duty as partners with us on this project; should you choose to accept…"

LEGO's Ideas, which focuses on ideation, and SeedInvest, which helps raise equity, could mitigate the negative effects of affiliation, for example, by describing initiatives as less communal and by posting updates with less communal language. Our findings are also applicable to crowdfunding contests (e.g., Camacho et al. 2019; Hurst 2017), where participants could be encouraged to vote across categories to reduce coparticipation and help them break away from the adverse effects of groupthink.

We highlight several areas of inquiry for future research. Reward structures could impact the role of affiliation in crowdfunding and thus merit attention (e.g., Sun, Dong, and McIntyre 2017). Fake reviews have been investigated in the online context (e.g., Zhao et al. 2013), and it would be interesting to explore the veracity of idea descriptions and creator updates. In addition to affiliation, which we study, other network characteristics such as clans and core–periphery structures (Wasserman and Faust 1999) could explain the nature of information flow across affiliation structures.

As interest in crowdfunding increases, interesting research questions continue to emerge. We believe that our research explores important questions concerning crowdfunding that involve backer affiliation and community structure, and we hope to lay the foundation for future studies in the domain.

Acknowledgements

The authors gratefully acknowledge feedback from Lopo Rego, Vivek Astvansh, Ashok Lalwani, Adriana Samper, Beth Fossen, Anwesha De, Ryan Elder, and Kristen Ferguson on a previous version of this article.

Author Contribution

The authors contributed equally to this research and are listed randomly.

Associate Editor

Hari Sridhar

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iDs

Girish Mallapragada https://orcid.org/0000-0001-7425-9793
Vishal Narayan https://orcid.org/0000-0001-7230-3084

References

Agrawal, Ajay, Christian Catalini, and Avi Goldfarb (2015), "Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions," *Journal of Economics & Management Strategy*, 24 (2), 253–74.

Allen, B.J., Deepa Chandrasekaran, and Suman Basuroy (2018), "Design Crowdsourcing: The Impact on New Product Performance of Sourcing Design Solutions from the 'Crowd'," *Journal of Marketing*, 82 (2), 106–23.

Allison, Thomas H., Blakley C. Davis, Jeremy C. Short, and Justin W. Webb (2015), "Crowdfunding in a Prosocial Microlending Environment: Examining the Role of Intrinsic Versus Extrinsic Cues," *Entrepreneurship Theory and Practice*, 39 (1), 53–73.

Bayus, Barry L. (2013), "Crowdsourcing New Product Ideas Over time: An Analysis of the Dell IdeaStorm Community," *Management Science*, 59 (1), 226–44.

Berger, Christoph, Martin Winkels, Alexander Lischke, and Jacqueline Höppner (2012), "GazeAlyze: a MATLAB Toolbox for the Analysis of Eye Movement Data," *Behavior Research Methods*, 44 (2), 404–19.

Buechel, Eva C. and Chris Janiszewski (2013), "A Lot of Work or a Work of Art: How the Structure of a Customized Assembly Task Determines the Utility Derived From Assembly Effort," *Journal of Consumer Research*, 40 (5), 960–72.

Burt, Ronald S. (1992), *Structural Holes: The Social Structure of Competition*. Boston: Harvard University Press.

Burtch, Gordon, Anindya Ghose, and Sunil Wattal (2013), "An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-funded Markets," *Information Systems Research*, 24 (3), 499–519.

Camacho, Nuno, Hyoryung Nam, P.K. Kannan, and Stefan Stremersch (2019), "Tournaments to Crowdsource Innovation: The Role of Moderator Feedback and Participation Intensity," *Journal of Marketing*, 83 (2), 138–57.

Clark, Margaret S. and Judson Mils (1993), "The Difference Between Communal and Exchange Relationships: What It Is and Is Not," *Personality and Social Psychology Bulletin*, 19 (6), 684–91.

Cowley, Stacy (2016), "Global Brands, Taking Cue from Tinkerers, Explore Crowdfunding," *The New York Times* (January 6), https://www.nytimes.com/2016/01/07/business/global-brands-taking-cue-from-tinkerers-explore-crowdfunding.html.

Dai, Hengchen and Dennis J. Zhang (2019), "Prosocial Goal Pursuit in Crowdfunding: Evidence from Kickstarter," *Journal of Marketing Research*, 56 (3), 498–517.

Decety, Jean and Julie Grèzes (2006), "The Power of Simulation: Imagining One's Own and Other's Behavior," *Brain Research*, 1079 (1), 4–14.

Durbin, Joe (2017), "The Oculus Acquisition May Cost Facebook $3 Billion, Not $2.3 Billion," *Upload* (January 19), https://uploadvr.com/oculus-acquisition-3-billion/.

Eckhardt, Giana M., Mark B. Houston, Baojun Jiang, Cait Lamberton, Aric Rindfleisch, and Georgios Zervas (2019), "Marketing in the Sharing Economy," *Journal of Marketing*, 83 (5), 5–27.

Fan, Tingting, Leilei Gao, and Yael Steinhart (2020), "The Small Predicts Large Effect in Crowdfunding," *Journal of Consumer Research*, 47 (4), 544–65.

Faust, Katherine (1997), "Centrality in Affiliation Networks," *Social Networks*, 19 (2), 157–91.

Fiske, Alan P. (1992), "The Four Elementary Forms of Sociality: Framework for a Unified Theory of Social Relations," *Psychological Review*, 99 (4), 689–723.

Gerber, Elizabeth M. and Julie Hui (2014), "Crowdfunding: Motivations and Deterrents for Participation," *ACM Transactions on Computer-Human Interaction*, 20 (6), 24–32.

Germann, Frank, Peter Ebbes, and Rajdeep Grewal (2015), "The Chief Marketing Officer Matters!" *Journal of Marketing*, 79 (3), 1–22.

Goenka, Shreyans and Stijn M.J. Van Osselaer (2019), "Charities Can Increase the Effectiveness of Donation Appeals by Using a Morally Congruent Positive Emotion," *Journal of Consumer Research*, 46 (4), 774–90.

Goldstein, Noah J. and Robert B. Cialdini (2007), "The Spyglass Self: A Model of Vicarious Self-Perception," *Journal of Personality and Social Psychology*, 92 (3), 402–17.

Hong, Yili, Yuheng Hu, and Gordon Burtch (2018), "Embeddedness, Prosociality, and Social Influence: Evidence from Online Crowdfunding," *MIS Quarterly*, 42 (4), 1211–24.

Hou, Rui, Leiming Li, and Bingquan Liu (2020), "Backers Investment Behavior on Explicit and Implicit Factors in Reward-Based Crowdfunding Based on ELM Theory," *PLoS One*, 15 (8), e0236979.

Hurst, Samantha (2017), "Motorola Announces: Indiegogo-Collaborated 'Transform the Smartphone' Challenge Finalists Have Been Selected," *Crowdfund Insider* (February 9), https://www.crowdfundinsider.com/2017/02/95919-motorola-announces-indiegogo-collaborated-transform-smartphone-challenge-finalists-selected/.

Imai, Susumu, Neelam Jain, and Andrew Ching (2009), "Bayesian Estimation of Dynamic Discrete Choice Models," *Marketing Science*, 77 (6), 1865–99.

Khan, Uzma and Ravi Dhar (2006), "Licensing Effect in Consumer Choice," *Journal of Marketing Research*, 43 (2), 259–66.

Kim, Chul, P.K. Kannan, Michael Trusov, and Andrea Ordanini (2020), "Modeling Dynamics in Crowdfunding," *Marketing Science*, 39 (2), 339–65.

Kim, Cheonsoo and Sung-Un Yang (2017), "Like, Comment, and Share on Facebook: How Each Behavior Differs from the Other," *Public Relations Review*, 43 (2), 441–49.

Kouchaki, Maryam (2011), "Vicarious Moral Licensing: The Influence of Others' Past Moral Actions on Moral Behavior," *Journal of Personality and Social Psychology*, 101 (4), 702–15.

Kuppuswamy, Venkat and Barry L. Bayus (2017), "Does My Contribution to Your Crowdfunding Project Matter?" *Journal of Business Venturing*, 32 (1), 72–89.

Leary, Mark R. (2010), "Affiliation, Acceptance, and Belonging: The Pursuit of Interpersonal Connection," in *Handbook of Social Psychology*, Vol. 2, 5th ed. D.T. Gilbert, G. Lindzey, and S.T. Fiske, eds. Hoboken, NJ: John Wiley & Sons.

Li, Gen and Jing Wang (2019), "Threshold Effects on Backer Motivations in Reward-Based Crowdfunding," *Journal of Management Information Systems*, 36 (2), 546–73.

Lin, Mingfeng, Nagpurnanand R. Prabhala, and Siva Viswanathan (2013), "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending," *Management Science*, 59 (1), 17–35.

Mallapragada, Girish, Rajdeep Grewal, and Gary Lilien (2012), "User-Generated Open Source Products: Founder's Social Capital and Time to Product Release," *Marketing Science*, 31 (3), 474–92.

Matthews, William John, Ana I. Gheorghiu, and Mitchell J. Callan (2016), "Why Do We Overestimate Others' Willingness to Pay?" *Judgment and Decision Making*, 11 (1), 21–39.

Meijers, Marijn H.C., Marret K. Noordewier, Peeter W.J. Verlegh, Simon Zebregs, and Edith G. Smit (2019), "Taking Close Others' Environmental Behavior into Account When Striking the Moral Balance? Evidence for Vicarious Licensing, Not for Vicarious Cleansing," *Environment and Behavior*, 51 (9/10), 1027–54.

Moradi, Masoud and Mayukh Dass (2019), "An Investigation into the Effects of Message Framing on Crowdfunding Funding Level," *Journal of Electronic Commerce Research*, 20 (4), 238–54.

Morewedge, Carey K., Meng Zhu, and Eva C. Buechel (2019), "Hedonic Contrast Effects are Larger when Comparisons are Social," *Journal of Consumer Research*, 46 (2), 286–306.

Nair, Harikesh S., Puneet Manchanda, and Tulikaa Bhatia (2010), "Asymmetric Social Interactions in Physician Prescription Behavior: The Role of Opinion Leaders," *Journal of Marketing Research*, 47 (5), 883–95.

Narayan, Vishal and Vrinda Kadiyali (2016), "Repeated Interactions and Improved Outcomes: An Empirical Analysis of Movie Production in the U.S.," *Management Science*, 62 (2), 591–607.

Netzer, Oded, Alain Lemaire, and Michal Herzenstein (2019), "When Words Sweat: Identifying Signals for Loan Default in the Text of Loan Applications," *Journal of Marketing Research*, 56 (6), 960–80.

Newman, Kevin P. and Merrie Brucks (2018), "The Influence of Corporate Social Responsibility Efforts on the Moral Behavior of High Self-Brand Overlap Consumers," *Journal of Consumer Psychology*, 28 (2), 253–71.

Papies, Dominik, Peter Ebbes, and Harald J. van Heerde (2017), "Addressing Endogeneity in Marketing Models," in *Advanced Methods for Modeling Markets*, J.E. Wieringa, K.H. Pauwels, P.S.H. Leeflang, and T.H.A Bijmolt, eds. Berlin: Springer.

Park, Eunho, Rishika Rishika, Ramkumar Janakiraman, Mark B. Houston, and Byungjoon Yoo (2018), "Social Dollars in Online Communities: The Effect of Product, User, and Network Characteristics," *Journal of Marketing*, 82 (1), 93–114.

Pennebaker, James W., Ryan L. Boyd, Kayla Jordan, and Kate Blackburn (2015), *The Development and Psychometric Properties of LIWC2015*. Austin: University of Texas.

Pietraszkiewicz, Agnieszka, Birthe Soppe, and Magdalena Formanowicz (2017), "Go Pro Bono: Prosocial Language as a Success Factor in Crowdfunding," *Social Psychology*, 48 (5), 265–78.

Ransbotham, Sam, Gerald C. Kane, and Nicholas H. Lurie (2012), "Network Characteristics and the Value of Collaborative User-Generated Content," *Marketing Science*, 31 (3), 387–405.

Rossi, Peter E. (2014), "Even the Rich Can Make Themselves Poor: A Critical Examination of IV Methods in Marketing Applications," *Marketing Science*, 33 (5), 655–72.

Simpson, Bonnie, Martin Schreier, Sally Bitterl, and Katherine White (2021), "Making the World a Better Place: How Crowdfunding Increases Consumer Demand for Social-Good Products," *Journal of Marketing Research*, 58 (2), 363–76.

Sridhar, Shrihari, Frank Germann, Charles Kang, and Rajdeep Grewal (2016), "Relating Online, Regional, and National Advertising to Firm Value," *Journal of Marketing*, 80 (4), 39–55.

Srinivasan, Raji, Stefan Wuyts, and Girish Mallapragada (2018), "Corporate Board Interlocks and New Product Introductions," *Journal of Marketing*, 82 (1), 132–48.

Stalder, Hannah and Sarah-Jane Stenson (2016), "Unilever Foundry and Indiegogo Launch Crowdfunding Partnership To Accelerate Innovation," Unilever (March 8), https://www.unileverusa.com/news/press-releases/2016/unilever-foundry-and-indiegogo-launch-crowdfunding-partnership.html.

Statista (2021), "Crowdfunding - Statistics & Facts," (accessed May 5, 2021), Available at: https://www.statista.com/topics/1283/crowdfunding/.

Stock, James H., Jonathan H. Wright, and Motohiro Yogo (2002), "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business & Economic Statistics*, 20 (4), 518–29.

Sun, Yacheng, Xiaojing Dong, and Shelby McIntyre (2017), "Motivation of User-Generated Content: Social Connectedness Moderates the Effects of Monetary Rewards," *Marketing Science*, 36 (3), 329–37.

Sunder, Sarang, Kihyun Hannah Kim, and Eric A. Yorkston (2019), "What Drives Herding Behavior in Online Ratings? The Role of Rater Experience, Product Portfolio, and Diverging Opinions," *Journal of Marketing*, 83 (6), 93–112.

Swaminathan, Vanitha and Christine Moorman (2009), "Marketing Alliances, Firm Networks, and Firm Value Creation," *Journal of Marketing*, 73 (5), 52–69.

Tian, Kelly T., William O. Bearden, and Gary L. Hunter (2001), "Consumers' Need for Uniqueness: Scale Development and Validation," *Journal of Consumer Research*, 28 (1), 50–66.

Wasserman, Stanley and Katherine Faust (1999), *Social Network Analysis: Methods and Applications*. Cambridge, UK: Cambridge University Press.

Watts, Duncan J. (1999), "Networks, Dynamics, and the Small-World Phenomenon," *American Journal of Sociology*, 105 (2), 493–527.

Wei, Yanhao "Max", Jihoon Hong, and Gerard J. Tellis (2021), "Machine Learning for Creativity: Using Similarity Networks to Design Better Crowdfunding Projects," *Journal of Marketing* (published online March 9), https://doi.org/10.1177/00222429211005481.

Wessling, Kathryn Sharpe, Joel Huber, and Oded Netzer (2017), "MTurk Character Misrepresentation: Assessment and Solutions," *Journal of Consumer Research*, 44 (1), 211–30.

Xiang, Diandian, Leinan Zhang, Qiuyan Tao, Yonggui Wang, and Shuang Ma (2019), "Informational or Emotional Appeals in Crowdfunding Message Strategy: An Empirical Investigation of Backers' Support Decisions," *Journal of the Academy of Marketing Science*, 47 (6), 1046–63.

Younkin, Peter and Venkat Kuppuswamy (2017), "The Colorblind Crowd? Founder Race and Performance in Crowdfunding," *Management Science*, 64 (7), 3269–87.

Zhang, Juanjuan and Peng Liu (2012), "Rational Herding in Microloan Markets," *Management Science*, 58 (5), 892–912.

Zhao, Yi, Sha Yang, Vishal Narayan, and Ying Zhao (2013), "Modeling Consumer Learning From Online Product Reviews," *Marketing Science*, 32 (1), 153–69.