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Do Backer Affiliations Help or Hurt Crowdfunding Success?

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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. We find that while an increase in the total number of backers may positively affect funding behavior, the resulting affiliations affect funding negatively. We 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. Based on data collected from 2,021 ideas on a prominent crowdfunding platform, we 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. We develop actionable insights for creators to mitigate the negative effects of affiliation with the language used in idea descriptions and updates.

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

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 3 billion USD (Durbin 2017). Peloton, the highly successful exercise bike, started as a Kickstarter project. The global crowdfunding market is expected to be well over 40 billion USD 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 et al. 2018; Dai and Zhang 2019). Crowdfunding is a form of crowdsourcing in which participants, henceforth referred to as backers, are recruited to raise funds for ideas (e.g., Fan et al. 2020; Wei et al. 2021). As some backers fund the same ideas, i.e., co-back, 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 co-backing 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.

[Insert Figure 1 about here]

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). Past research shows that attracting more backers positively impacts crowdfunding outcomes (Hou et al. 2020), an insight that many creators seem to grasp. However, crowd size does not represent the social structure, i.e., the pattern of connections in the community. In crowdfunding, as in other contexts where shared communal goals exist (e.g., Wikipedia), social structure plays a more prominent role (e.g., Ransbotham et al. 2012; Wei et al. 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, hence, the idea's funding success.

Affiliation is a powerful force as it makes affiliated others' actions lead to changes in one's subsequent behavior (e.g., Mallapragada et al. 2012; Sunder et al. 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 co-backing, creators and backers also engage through non-monetary 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 et al. 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 seek 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 datasets, including secondary data and experiments, to provide convergent validity to our findings. We also conduct interviews with six 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 dataset 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 co-backing relationships of backers who back on the focal day, with backers who funded until the day before the focal day (e.g., Mallapragada et al. 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. For the first time, we 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 83 USD/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 36 USD/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 when 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

While crowdfunding emerges as a dominant force for funding new ideas, research on crowdfunding is limited. Most early research focused on microlending (Lin et al. 2013; Zhang and Liu 2012) or on crowdfunding platforms for music and journalism (e.g., Agrawal et al. 2015; Burtch et al. 2013). Topics such as proximity to the deadline (Dai and Zhang 2019) and the text of content (e.g., Netzer et al. 2019) have also gathered 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 et al. 2013), geographic proximity (Agrawal et al. 2015), and social interactions (Kim et al. 2020). We present a summary of representative research in Table 1.

-- Insert Table 1 about here --

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 co-participation in events, in our case, co-backing 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 et al. 2018), product development (e.g., Mallapragada et al. 2012), and wiki contributions (Ransbotham et al. 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 et al. 2012; Sunder et al. 2019).

To establish that participants notice affiliated others' behavior when visiting crowdfunding platforms, we ran a pilot study with actual backers who we pre-screened based on 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 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 (see Web Appendix A for details). Discussions on crowdfunding message boards and websites, and 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 Turk 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 non-communal (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 non-communal (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 six 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 seek 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 et al. 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 et al. 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 et al. 2012). Updates might draw backers' attention to the idea's characteristics and evolution, and lessen attention towards co-backers 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 multi-method 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 where 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 18th December 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 link "community" 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

[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/ and https://www.piggybackr.com/.

dataset 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 non-informative. Next, we describe the key measures.

Daily amount funded. Consistent with prior literature (Agrawal et al. 2015; Burtch et al. 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 et al. 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 co-backing 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 co-backing 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 co-backing relationship represents one unit of affiliation. Affiliation increases both with the number of backers who co-back and with the number of co-backed ideas.

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 funded another idea *j*. As there is one co-backing relationship (that between Jack and Tom for co-backing 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 funded another idea *j*. Furthermore, before December 17, Jill and Tom both funded another idea *k*. As there are two co-backing relationships (those between Jack and Tom for co-backing idea *j*, and between Jill and Tom for co-backing 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 co-backing relationships (those between Jack and Tom for co-backing idea *j*, and between Jack and Jane for co-backing 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 only have 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 6 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 co-backing 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 "co-backed ideas" or the number of "common backers." Other measures are likely sparser than our measure. Later, 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. These regimes are 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 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 co-backing 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.

-- Insert Table 2 and Table 3 about here –

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

$$\log(y_{it}) = \alpha_i + \alpha_t + \beta_1\log(Affil_{it-1}) + \beta_2\log(CumBackers_{it-1}) + \beta_3\log(CumUpdates_{it-1}) + \beta_4\log(y_{it-1}) + \beta_5 PropGoal_{it-1} + \beta_6 PropDuration_{it-1} + \beta_7 LastWeek_{it-1} + \beta_8 Network_{it-1} + \beta_9 log(CommunalUpdates_{it-1}) + \beta_{10}\log(Affil_{it-1}) \text{ X } CommunalUpdates_{it-1} + \beta_{11}\log(Affil_{it-1}) \text{ X } FBShares_i + \varepsilon_{it} \quad (1)$$

To account for non-negativity, 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 0.001. 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, etc., we employ idea-specific fixed effects α_i, a vector of 2,021 elements for the Kickstarter dataset. 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 co-backing relationships between those backers who fund idea *i* on day *t-1* and all backers who have funded this idea before day *t-1*. Later 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 et al. 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 now discuss other time-varying idea-specific controls. First, the number of affiliations among backers is correlated 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*. Additionally, $CommunalUpdates_{it-1}$ is the number of communal words contained in the updates.

Third, the funding window of an idea influences its funding outcomes. Ideas receive higher 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 *i*, which 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. As these measures capture the extent of social capital that accrues to ideas due to being associated with certain backers, we seek 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 et al. 2012; Ransbotham et al. 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 that version of each measure, which 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 $CommunalUpdates_{it-1}$[4], and with the number of Facebook shares of the idea by backers ($FBShares_i$).

We use lags of all covariates as 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 variables in Table 4; most correlations are less than 0.3, allaying multicollinearity's ill-effects.

-- Insert Table 4 about here --

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 et al. 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 quite conclusively documented positive peer effects across various consumer contexts (e.g., Sunder et al. 2019; Zhang and Liu 2012). If there are positive effects due to the

[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 co-backing relationships with each other.

[4] We transformed this variable, such that the transformed variable is 0 if $Affil_{it-1}$ X $CommunalUpdates_{it-1} = 0$; and the transformed variable is 1 if $Affil_{it-1}$ X $CommunalUpdates_{it-1} > 0$. Since $Affil_{it-1}$ X $CommunalUpdates_{it-1} = 0$ for 93.3% of all observations, this transformation does not majorly 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: a dummy for whether the funding goal has been met, the number of backers of the focal idea on the focal day, "backer propensity," a measure of how likely backers are to fund, and "backer longevity," a measure of how long backers have been active on the platform.

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, which 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 paper from other contexts. Additionally, our interest is less in modeling agent behavior (e.g., an individual's rating of a product in Sunder et al. (2019)) than in modeling product success (i.e., funding success of an idea). We now 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 et al. (2010) and Sunder et al. (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, which might be correlated with affiliation and funding. For example, affiliation and funding are both likely 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 earlier, 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 2SLS IV 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 later, where participants were randomly assigned to different affiliation levels, creating exogenous variation.

For the primary IV approach, we follow recent research (e.g., Germann et al. 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 Dec 22, this instrument is the mean of affiliations on Dec 22 of all ideas in our data, which 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, as 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:

$$log(Affil_{it-1}) = \lambda_0 + \lambda_1 IV_{it-1} + \lambda_2 log(CumBackers_{it-1}) + \lambda_3 log(CumUpdates_{it-1}) + \lambda_4 log(y_{it-1}) + \lambda_5 PropGoal_{it-1} + \lambda_6 PropDuration_{it-1} + \lambda_7 LastWeek_{it-1} + \lambda_8 Network_{it-1} + \lambda_9 log(CommunalUpdates_{it-1}) + \delta_{it-1} \quad (2)$$

The R^2 for the first stage regression without the instrument (i.e., assuming $\lambda_1 = 0$) is 0.365 and with the instrument is 0.385, 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 et al. 2002, p. 522). The large value of the Anderson-Rubin statistic ($F(1, 28300) = 298.41$) 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 ($CommunalUpdates_{it-1}$). Following Papies et al. (2017), the instrument for this interaction variable is the interaction of the instrument for affiliation and $CommunalUpdates_{it-1}$. We do not instrument for the interaction of affiliation and the number of Facebook shares as the Durbin-Wu-Hausman test of the hypothesis that this regressor is exogenous could not be rejected ($\chi^2 = 0.055$; $p > .1$). 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 IV 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 to 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 next discuss.

Full Model Results. We find that affiliation among backers has a consistent negative effect on the funding of ideas on Kickstarter (β = -.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.

-- Insert Table 5 about here --

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 (β = -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 (β = -.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 (β= 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 et al. 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 co-backing, 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 (β =

-.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 to 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 et al. 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 10 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, 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 where 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 the study on Amazon Turk with 200 North American residents[6] (M_{Age} = 35.26 years, 49.8% women; 42.6% of whom have previously funded a crowdfunding idea). We presented participants with two ideas seeking funding (both real 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 et al. 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 et al. 2019). Participants were told, "As part of this study, you will receive a $2

[6] Because this study involved real pay, we restricted participants to not include those who had completed over 1500 studies as these "professional" Amazon Turkers may behave in significantly different ways, particularly when monetary bonuses are included (Wessling et al. 2017).

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 9-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 Amazon Turk 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. Then, they saw a screenshot of a second website designed to look like an idea on a crowdfunding platform; see Web Appendix I for details.

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 9-point scale ranging from $0 to $2.00 in $.25 intervals served as the outcome. At the end of the study, participants were given the money that they chose to keep as a bonus, and the remainder (i.e., what they chose to fund each of the ideas) was put toward each crowdfunding idea. Finally, participants responded to a set of demographic measures (e.g., age, gender, and whether they had previously funded an idea on a crowdfunding platform). A one-way ANOVA showed a significant effect of affiliation on the funding of the second idea ($F(1, 99) = 4.05$, $p < .05$). As 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 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 Amazon Turk with 228 North American residents ($M_{\text{Age}} = 39.57$ years, 54.4% women; 38.2% of whom have 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, non-profits, and 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 co-backers, I do not feel the need to fund [focal idea]" and "Based on the funding behavior of co-backers, 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 et al. 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 ANOVA showed a significant effect of affiliation on the licensing measure ($F(1, 223) = 3.89$, $p = .05$). As 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% CI does not include 0: -.4423, - .0003), but uniqueness was not (95% CI: -.5479, .1142).

In this experiment, we replicated the negative effect of affiliation and uncovered vicarious moral licensing as an underlying mechanism. While 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 this experiment, 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 Amazon Turk with 206 North American residents (M_{Age} = 38.81 years, 46.1% women; 42.2% of whom 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 et al. 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 which are 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 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} = \$2155.32, SD = \$3998.08 vs. $M_{control}$ = \$4073.04, SD = \$5316.08; $t(199) = 2.09$, $p < .04$). When the idea was described as *less communal*, there was no effect of affiliation on funding (M_{high} = \$2572.33, SD = \$4933.01 vs. $M_{control}$ = \$1868.68, SD = \$4039.03; $t(199) = -1.34$, $p = .18$; 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 earlier, 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 et al. 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 (mean is 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. Splitting the data based on the average number of communal words instead of the median does not affect the result. 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 validate 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 because these affiliated others are funding the idea (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 past 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 83 USD/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 36 USD/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 the paper. 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 re-evaluate 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 0.42% and translates to a decline of 1.72 USD/day.

We developed recommendations for creators and examples of best practices from our dataset (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.

-- Insert Table 6 about here --

Our results about the mechanism provide insights on how platforms and creators should engage with backers. Research has shown that licensing is a non-conscious 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 vicarious licensing might overwhelm other relevant idea information, potentially leading to suboptimal backer decisions. Based on our findings, backers might, in some cases, pay more attention to signals from affiliated others compared to 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. Others such as Sellaband and PledgeMusic, which were once popular, 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 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 co-back 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, based 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 LEGO's Ideas, which focuses on ideation, and SeedInvest, which helps raise equity, could mitigate the ill-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 co-participation 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 hence merit attention (e.g., Sun et al. 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 continues to increase, 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.

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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 & backer engagement	- FE Log-Linear Regression - Endogeneity (Instrument) - Robustness checks: Probit, Logit, and Tobit	Crowdfunding *Kickstarter* *Experiments*	Yes; 3 experiments	Prior backer affiliation decreases funding, negative effect due to vicarious moral licensing; effect stronger for ideas with communal descriptions and 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 being novel and imitative are balanced, optimal funding level closer to level of similar ideas.
Netzer, Lemaire and Herzenstein (2019)	Loan payback	- Loan descriptions	- 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.
Chul et al. (2019)	Goal Completion	- Forward-looking - Social interactions	- Bayesian IJC - Two-step - Counterfactuals	Crowdfunding (Music) *Sellaband*	No	Forward-looking investment behavior, contemporaneous and forward-looking social interactions impact share purchases and goal completion.
Burtch et al. (2016)	Contributions	- Concealment - Social norms	- Tobit - Endogeneity (IV)	Crowdfunding *Dataset undisclosed*	No	Concealment hurts the likelihood of contribution and contribution. Social norms drive concealment.
Agrawal et al. (2015)	Decision to invest	- Geography	- Linear regression - Fixed Effects	Crowdfunding (Music) *Sellaband*	No	Local backers are not influenced by artist. Effect does not persist past the first investment, indicates 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) *Dataset undisclosed*	No	Partial crowding-out effect, backers experience the 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, post-publication of the story.
Lin et al. (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.

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}$)	.31	.24	0	.27	.97
Closeness centrality of idea *i* as of day *t-1*	5.67×10^{-9}	5.01×10^{-8}	3.49×10^{-11}	2.50×10^{-10}	2.2×10^{-6}
Betweenness centrality of idea *i* as of day *t-1*	1258.07	8698.49	0	0	335,213
Eigenvector centrality of idea *i* as of day *t-1*	0.002	0.03	0	2.50×10^{-9}	1
Last week (1 if day *t* is in the last week of funding of idea *i*, 0 otherwise)	0.08	0.28	0	0	1
Cumulative number of communal words in updates by creator of idea *i* by day *t-1* ($CommunalUpdates_{it-1}$)	20.17	1696.27	0	0	230,232

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}) ≤ \$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	1178.21	5974.58
Eigenvector centrality of idea *i* as of day *t-1*	0.001	0.000	0.012
Last week (1 if day *t* is in the last week of funding of idea *i*, 0 otherwise)	0.10	0.07	0.06
Cumulative number of communal words in updates by creator of idea *i* by day *t-1* ($CommunalUpdates_{it-1}$)	0.69	1.93	199.38

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

No.	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 0.001. All variables pertain to the focal idea. Coefficients with $p < 0.05$ are in bold.

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*** (.01)	-.86*** (.06)	-1.88*** (.41)	-.80*** (.06)	**-.87*** (.06)**
Cumulative number of backers funding idea *i* by day *t-1* ($CumBackers_{it-1}$)	.15** (.06)	1.92*** (.15)	4.13*** (.90)	1.79*** (.15)	**2.02*** (.16)**
Cumulative number of updates by creator of idea *i* by day *t-1* ($CumUpdates_{it-1}$)	-.05** (.02)	-.06** (.03)	-.07* (.04)	-.06** (.03)	**-.05* (.03)**
Amount of funding of idea *i* (in $) on day *t-1*	-.03 (.02)	.01 (.02)	0.07** (0.03)	0.01 (0.02)	**0.01 (0.02)**
Proportion of funding goal of idea *i* achieved by day *t-1*	-.09 (.06)	-.23*** (.07)	-.39** (.10)	-.22** (.07)	**-.17** (.07)**
Proportion of funding duration of idea *i* completed by day *t-1*	-.27 (.99)	1.12 (1.10)	2.84* (1.65)	1.02 (1.09)	**.63 (1.10)**
Closeness centrality of idea *i* as of day *t-1*	2.54 (3.12)	2.43 (3.54)	8.46 (5.30)	1.99 (3.48)	**2.71 (3.54)**
Betweenness centrality of idea *i* as of day *t-1*	-.02** (0.01)	-.02** (0.01)	-.03* (.02)	-.02** (.01)	**-.02* (0.01)**
Eigenvector centrality of idea *i* as of day *t-1*	-.74 (.82)	-4.39* (2.33)	-8.95* (4.66)	-4.13* (2.21)	**-4.40* (2.67)**
Last week (1 if day *t* is in the last week of funding of idea *i*, 0 otherwise)	.25 (.21)	.13 (.24)	.03 (.35)	.14 (.24)	**.09 (.25)**
Cumulative number of communal words in updates by creator of idea *i* by day *t-1* ($CommunalUpdates_{it-1}$)	-.04 (.03)	-.02 (.03)	-.01 (.04)	-.02 (.03)	**-.29* (.15)**
Interactions of Backer Affiliations					
$Affil_{it-1}$ X $CommunalUpdates_{it-1}$					**-7.68** (3.80)**
$Affil_{it-1}$ X 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**

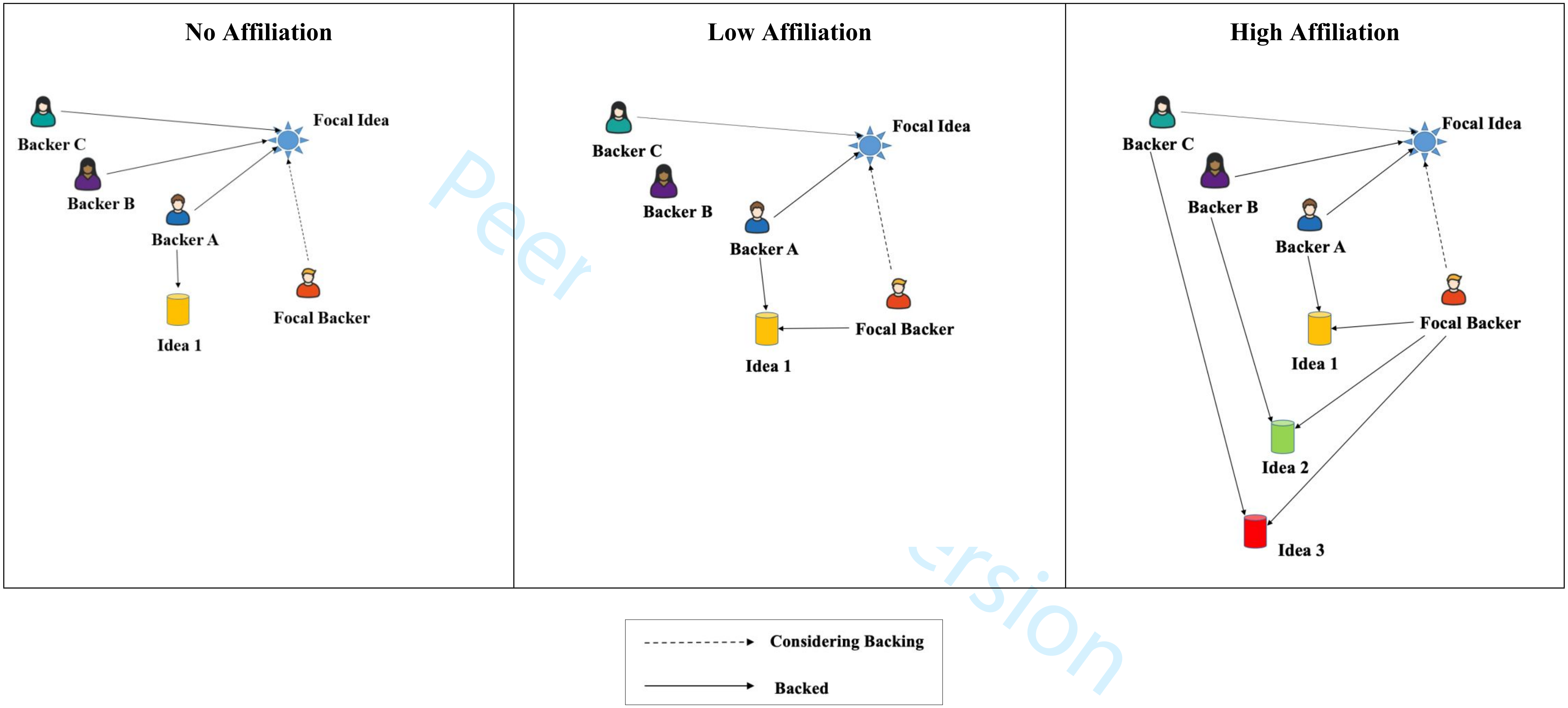
*** $p < .01$, ** $p < .05$, * $p < .10$

Notes: "Constra" refers to Burt's measure of constraint (Burt 1992) of the focal idea. "Other" instrument refers to the instrument constructed from Indiegogo data.

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 non-communal 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..."

Figure 1. Illustration of Affiliation in Crowdfunding



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; hence, there is no affiliation. In the second scenario, the focal backer and backer A have previously jointly funded idea 1; hence, there is 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.

Crowdfunding Success: Do Backer Affiliations Help or Hurt?

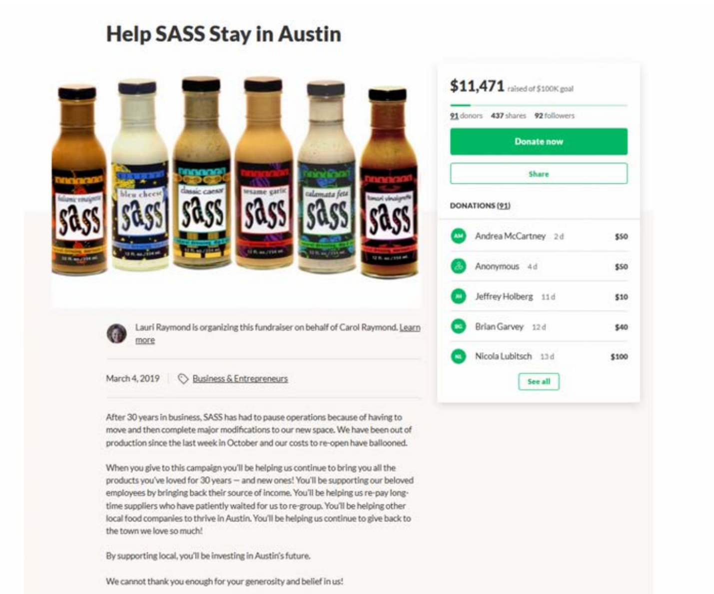
Kelly Herd, Girish Mallapragada, Vishal Narayan

List of Web Appendices

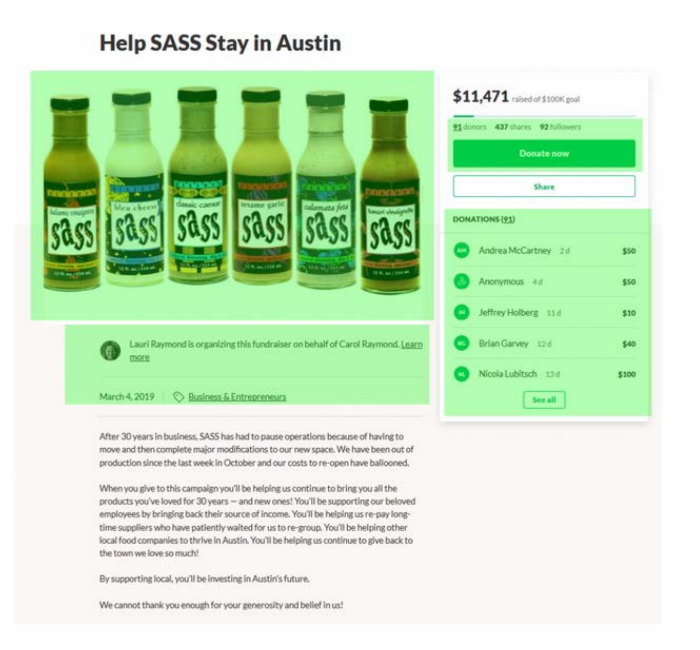
Web Appendix A. Heat Map Study

We conducted the study on Amazon Turk with 100 North American residents (M_{Age} = 38.36 years, 37% women). All participants read the following:

Below, you will see the GoFundMe page for SASS, out of Austin, Texas. There is lots of information available, and we are interested in what information you think is most relevant to your decision whether or not to fund. As you read about this project, please click on any information as you are reading it.



Participants then clicked on the sections as they read them:



Sixty-four participants reported reading at least one piece of information available on the idea page, including the following (in order of total across all participants):

1. Idea description (56)
2. User comments (43)
3. Creator updates (42)
4. Project image (39)
5. Total amount raised so far (38)
6. **Information about other funders (32)**
7. Organizer and beneficiary (28)
8. Creator name + date created (26)
9. Website Footer (25)
10. Donate Now + Total number of donors, shares, and followers (23)
11. Project title (18)

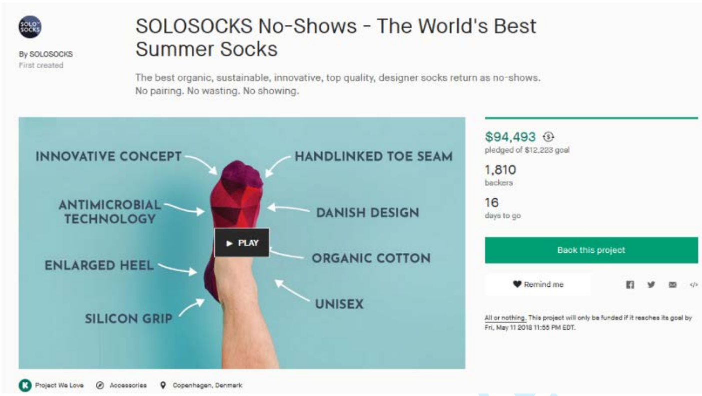
Next, we asked all participants to rank the following backer level variables from 1 = most important to 7 = least important. Averaging the rankings across all participants reveals that co-backing is perceived as more important than other seemingly important information such as backer location and community engagement:

1. Prior Projects Funded
2. Projects Created
3. **Co-backing Relationship (i.e., Whether a backer has funded other projects that you have also funded)**
4. Backer Location
5. Number of Comments Since Joining Community
6. Last Login
7. Username

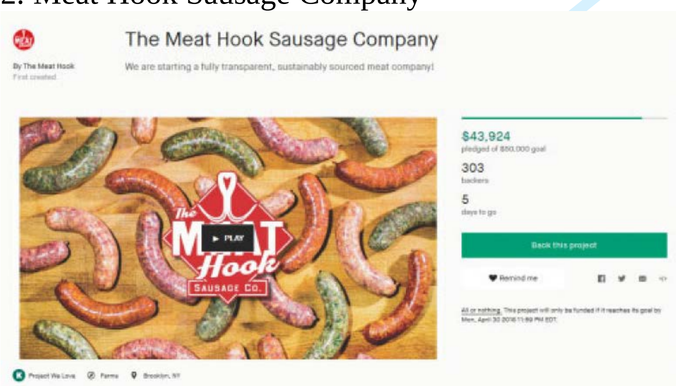
Web Appendix B. Affiliation and Shared Identity Study

To confirm that affiliation does indeed change perceptions of shared identity, an important driver of vicarious moral licensing (Goldstein and Cialdini 2007; Kouchaki 2011), we ran a study with 150 Amazon Turk participants (M_{Age} = 36.68 years, 48% women). First, 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:

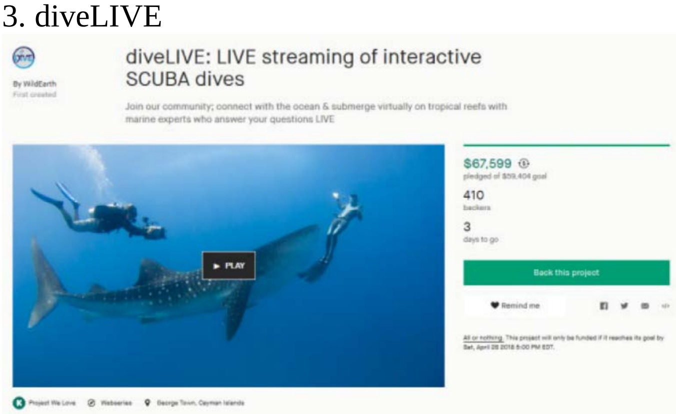
1. SoloSocks



2. Meat Hook Sausage Company



3. diveLIVE



4. Vision Thru Art

Participants then reported their perceived shared identity with these individuals who had chosen to fund the same project (i.e., high affiliation) or not (i.e., no affiliation). First, on 7-point Likert scales (strongly disagree/strongly agree), they reported how much they felt a connection, would have things in common, would have similar interests, are more similar than different, and feel more connected to these individuals than to others in the Kickstarter community (M = 4.04, SD = 1.33; α = .93). Next, participants completed one well-established measure of closeness (i.e., shared identity) in which participants are shown concentric circles that overlap to varying degrees and asked to mark the picture that describes their degree of shared identity with these individuals (M = 3.31, SD = 1.57; Aron et al. 1992; Newman and Brucks 2018). As expected, those in the high affiliation condition felt a stronger shared connection (M_{high} = 4.54, SD = 1.10 vs. M_{no} = 3.56, SD = 1.35; $F(1, 148) = 23.55$ $p < .01$) and greater overlap than those in the no affiliation condition (M_{high} = 3.60, SD = 1.50 vs. M_{no} = 3.03, SD = 1.60; $F(1, 148) = 5.04$, $p <$ .03).

Web Appendix C. Backer Interviews, Survey, and Discussion Forums

Interviews with Backers

We conducted a series of semi-structured interviews with six backers (M_{Age} = 41.2 years, 33.3% women). Individuals were recruited for interviews after they responded to a brief request posted on LinkedIn and Facebook by the authors. The initial request only stated that we were interested in talking to people who had funded ideas on crowdfunding platforms. Participants varied across profession, including marketing professionals, academics, and artists; participants also included both frequent and infrequent backers, ranging from 1 to 15 total ideas funded. All of the interviews took place over Zoom and lasted between 20 and 30 minutes. Five of the six participants agreed to be recorded (transcripts are available upon request).

The major themes that emerged across the six interviews could be summarized as follows: All the individuals felt that a motivation to be part of a community and contribute to something bigger than themselves was instrumental to their participation. Some also opined that crowdfunding platforms allow others to find interesting projects and figure out how to be early adopters of technology. Most of them indicated that they observed others' behaviors on the platforms, particularly participation on the idea's page and Q&A with the creators. While we found they had mixed opinions about whether others would explicitly influence them, they all indicated that they thought others on the platforms would be affected by such views. There were mixed views about guilt concerning not funding projects; and a few stated that they shared ideas through their social media. It also seemed that they mostly looked to what is happening on the idea's page to make funding decisions.

Overall, based on the interviews, we found evidence that people look to backer behavior as they participate on the platform and gather most information from Q&A, idea description, creator engagement, and backer engagements. Below are some quotes that reflect each of these topics.

- Prosocial motivation to participate:
  - "I feel moral pressure to fund."
  - "It is a combination of I feel that helping and being part of a community makes sense."

- How they find projects:
  - "I found the early projects I funded when I heard about them in media."
  - "I am interested in technology and seek out innovative ideas."

- Observing other backers' behaviors and licensing:
  - "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 in this kind of the crowdfunding world – and so it's interesting to follow that rabbit trail and see 'oh this person supported this and look at what else they fund,' there are these other smaller microcosms of whatever that interest is."
  - "I notice who else is funding and see them on the page, sometimes engaging with the creator."

- "If I continue, then I would probably look for, you know, where else is this guy funding, you know? .... I would love to see because if I feel like he is funding or he or she is finding interesting projects, then I would go look to see what else they are funded. After all, I'm sure there's something in there which I've missed."
- "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."

Survey of Backers

We surveyed 100 backers (M_{Age} = 37.29 years, 30% women) who were pre-screened on prior crowdfunding behavior through Prolific, an online participant recruitment site.

First, we asked them to evaluate information found on a crowdfunding website (e.g., idea description, user comments). These participants then assessed each piece of information on a 7-point Likert scale (not important/very important). We found that while not as important as some other information, e.g., creator updates, "the presence of other co-backers (i.e., others who have funded ideas that you have previously funded)" is perceived as important, $M = 4.14$, which is significantly above the midpoint of the scale ($t(99) = 4.05$, $p = .000$).

Next, to further demonstrate that prosocial motives are prominent in crowdfunding contexts, we asked these backers about their motivation to donate. As expected, the desire to support a cause (64%), help others (48%), bring valuable products and services to the marketplace (64%), and be part of a community (25%) were prominent. Participants also reported the desire to gain financial returns (41%), collect rewards (41%), gain recognition (7%), and avoid boredom (4%). This suggests that while not all backers are motivated by purely prosocial goals, these goals are common. These findings are in line with findings from other research (e.g., Simpson et al. 2021).

To further validate our proposed mechanism, we explicitly asked participants how much they disagree/agree with three statements about affiliation and vicarious moral licensing.

- "Backers I overlap with on other ideas (i.e., those who have previously funded an idea that I fund) can inform my funding behavior" (1 = strongly disagree, 7 = strongly agree), $M = 4.27$. This is significantly above the midpoint ($t(99) = 5.12$, $p = .000$).
- "When other people with whom I have co-backed fund a new idea, I feel less of a need also to fund" (1 = strongly disagree, 7 = strongly agree), $M = 3.75$. This is marginally above the midpoint ($t(99) = 1.96$, $p = .053$).
- "When other people with whom I have co-backed fund a new idea, I sometimes feel justified in not funding" (1 = strongly disagree, 7 = strongly agree), $M = 3.84$. This is significantly above the midpoint (t(99) = 2.50, $p = .014$)

Taken together, we find that backers are often motivated by prosocial motives, and when affiliated others fund an idea, they felt less of a need to fund, further validating the proposed vicarious moral licensing mechanism.

Backer Discussion Forum Posts

We gathered 572 discussion posts from kickstarterforums.org on the following three relevant threads: 1) “How many ideas have you backed and why do you back them?” (n = 317), 2) “What’s the most interesting idea you’ve backed?” (n = 247), and 3) “What’s the worst idea you have backed? And why?” (n = 8). Next, we used text analysis (bag of words approach) to code conversations among backers.

We coded the posts on three dimensions established in the LIWC (2015) dictionary: communal, innovation, and exchange. Our goal was to see the relative emphasis of comments on communal compared to innovation, the dominant focus of crowdfunding platforms, and to exchange, another commonly discussed motive in crowdfunding. This dichotomy also maps onto our Experiment 3, where we look at the heterogeneity in the effect of affiliation depending on the idea’s description. We cross-validated each category’s words with those available in LIWC (2015) categories (Pennebaker et al. 2015). Consistent with our prediction that prosocial goals drive behavior in crowdfunding platforms, we see that participants were much more likely to use communal words (count = 582) than to discuss innovation (count = 230) or exchange-based motives (count = 13).

Results indicated that in addition to focusing on creator information, they do notice the behavior of backers and, as such, are motivated by a desire to feel like a part of a broader community:

- “Pebble watch was what got me into Kickstarter. Since then, I have backed 10 projects. I think the aggregate feeling I get from a project on 3 fronts: creativity, passion, and utility, determine if there is enough impulse to back a project. Some [projects] I simply have no connection within my realm, but the genuine presentation from the creator and the feeling that it will, on the net, bring goodness to the world will nudge my mouse towards the pledge button.”
- “I’ve backed 6 projects…I am astounded by some of the big backers out there.”
- “I’ve backed 12 projects so far. To be honest, I first started backing because I wanted others to back my new project. But now I’m hooked and wish I could afford to back a ton more. I love backing projects in general because the whole idea is just awesome. It really shows how powerful the internet can be when it’s used for something positive and helps foster the creative spirit.”

Web Appendix D. Summary Statistics For Kickstarter and Indiegogo Ideas

Table W1. Category Level Statistics for Kickstarter Ideas (N = 2021)

Category	Average Amount Goal	Average Facebook Shares	Number of Projects
Film & Video	59,211	169	1258
Music	11,918	140	1015
Publishing	12,151	91	880
Games	34,280	208	594
Art	12,913	92	576
Design	22,516	144	477
Fashion	12,735	276	409
Food	16,969	133	333
Technology	44,990	154	296
Comics	6,595	122	205
Theater	9,210	83	179
Photography	7,968	97	177
Dance	6,694	83	79

Table W2. Category Level Statistics for Indiegogo Ideas (N = 2012)

Category	Average Amount Goal	Average Facebook Shares	Number of Ideas
Film	41,996	130	495
Music	8,856	124	268
Theater	9,350	93	198
Art	16,689	97	147
Technology	255,190	488	127
Community	74,407	187	114
Small Business	35,027	102	94
Education	134,852	112	71
Video / Web	23,848	126	65
Writing	10,141	88	60
Design	507,389	210	54
Food	33,601	201	54
Dance	5,822	89	43
Health	132,370	67	39
Gaming	23,494	74	32
Photography	15,230	145	29
Fashion	16,050	98	25
Environment	115,826	126	23
Politics	2,148,968	49	17
Sports	378,643	286	15
Comic	6,156	86	14
Animals	49,007	53	12
Transmedia	28,356	82	9
Religion	46,804	19	6
Faith	500	0	1

Table W3. Summary Statistics for Indiegogo Ideas

Variable	Mean	SD	Min	Median	Max
Amount of funding of idea *i* (in $) on day *t*	447.82	2,371.82	0	125	122,507
Backer affiliation of idea *i* by day *t-1* ($Affil_{it-1}$)	.37	1.79	0	0	90
Cumulative number of backers funding idea *i* by day *t-1*($CumBackers_{it-1}$)	249.08	506.94	0	57	16,883
Cumulative number of updates by creator of idea *i* by day *t-1* ($CumUpdates_{it-1}$)	410.91	1726.96	0	97	13,949
Proportion of funding goal of idea *i* achieved by day *t-1* ($PropGoal_{it-1}$)	.52	1.94	0	.26	12.73
Proportion of funding duration of idea *i* completed by day *t-1* ($PropDuration_{it-1}$)	.42	.21	.01	.42	1

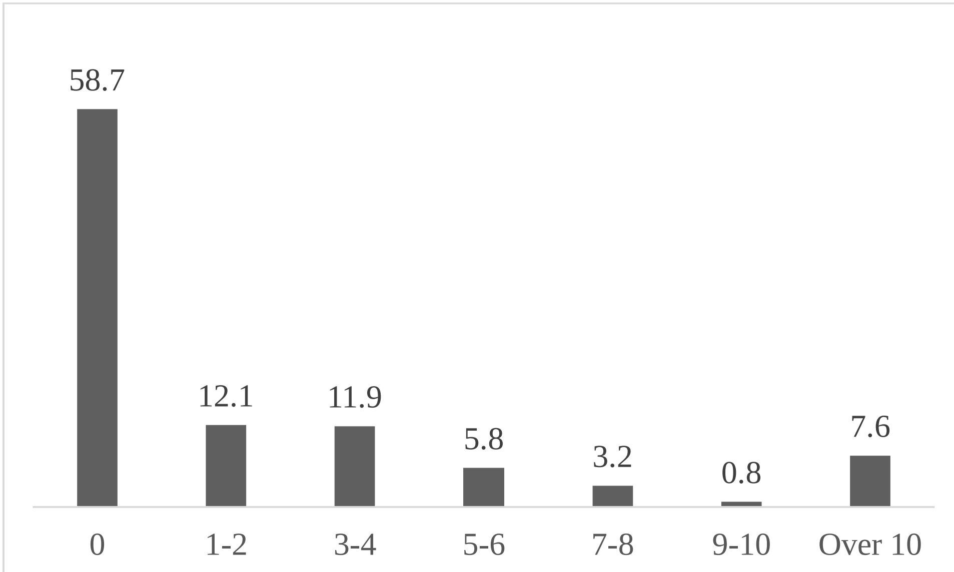
Web Appendix E. Figures and Illustrations Describing Data Sample

It is theoretically possible that affiliation is restricted to a small subset of ideas. We provide evidence that affiliation is commonly prevalent in our data. We first show (in Figure A1) that affiliation takes zero values for less than 60% of idea-day level observations and that the proportion of observations with very high values of affiliation (greater than 10) is only about 8%. Next, we show (in Figure A2) that at an idea level, the mean value of affiliation (across days) exceeds zero for over 1,500 out of 2,201 ideas and that the mean value of affiliation exceeds 10 for just 183 ideas. Figure A3 shows that the mean level of affiliation varies substantially across categories (between 2.3 and 4.6), but that it does not take extremely high or extremely low values for any one category.

To analyze temporal trends, we plot the mean value (across ideas) of affiliation across days of the funding window (Figure A4). We find an increasing trend of affiliation over the funding window and note that this increase is not monotonic. For some days, the mean level of affiliation is lower than that in the previous day. Our results are unaffected by this trend since we incorporate day-specific fixed effects. We notice a similar trend when we plot the mean of the ratio of affiliation to the number of backers for each day of the funding window (Figure A5). All figures appear at the end of this document.

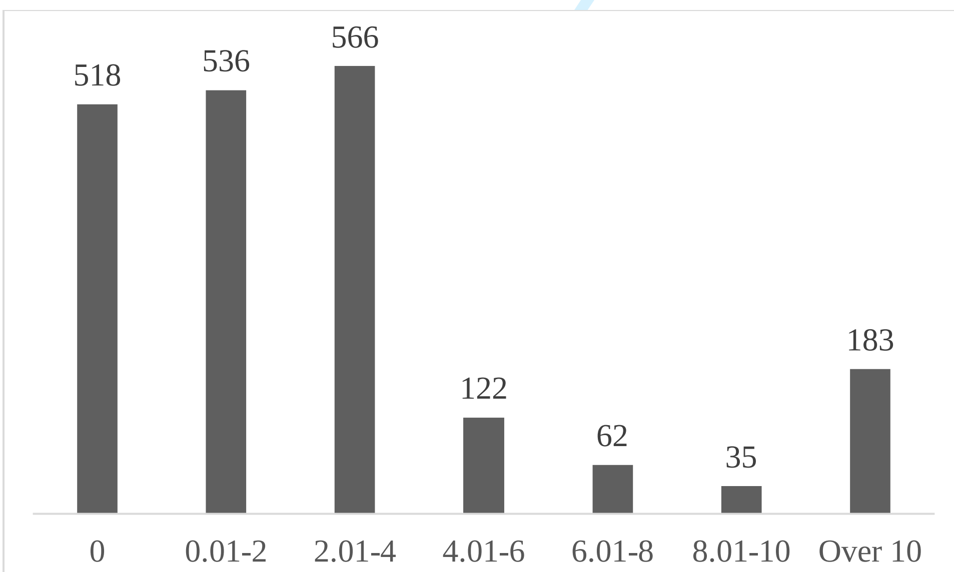
In addition to statistics about affiliation and to provide visual intuition, we graphed the network structure on day 1, day 18, and day 37 using a bipartite network representation – i.e., both projects (green nodes) and backers (pink nodes) are visible. Please see Figures A6 and A7. As a thought experiment, if there were no affiliation, each project would gather some stand-alone backers and end up as an island. On the contrary, the graphs show that over time, affiliations become the basis for the community and crowd-behavior to play out. Although some projects remain as islands, i.e., their backers have no affiliations with others, these decline over time as affiliations continue to increase. On day 1, 4 out of 34 projects (i.e., about 11%) are part of the continuously connected giant component of the network, i.e., these projects are not islands. By day 18, this number is 486 out of 1033 projects (47%). By the last day of our data collection, most projects – 1921 out of 2587 (74%) are not islands and are part of one continuously connected component due to affiliations.

Figure W1. Distribution of Affiliation Measure Across Idea-Day Level Observations (% of observations for various levels of affiliation)



Note: to be read as "affiliation for 12.1% of observations is 1 or 2; affiliation for 7.6% of observations is 10 or more"

Figure W2. Distribution of Mean Daily Affiliation Across Ideas (number of ideas for various levels of mean affiliation)



Note: to be read as "across all days that ideas sought funding, the mean daily affiliation for 566 ideas is between 2.01 and 4"

Figure W3. Mean Daily Affiliation for Each Category of Ideas

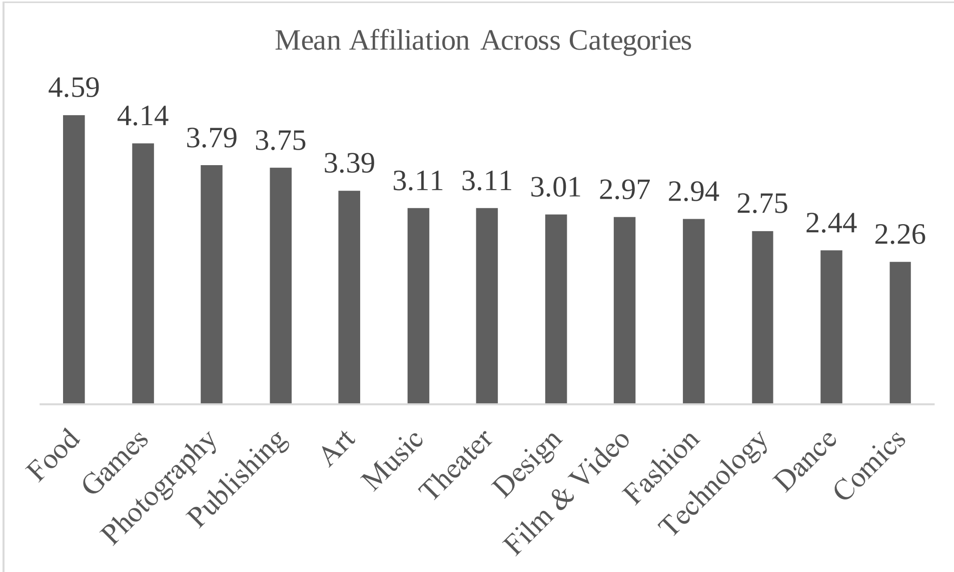


Figure W4. Mean Affiliation (Across Ideas) For Each Day of Funding Window

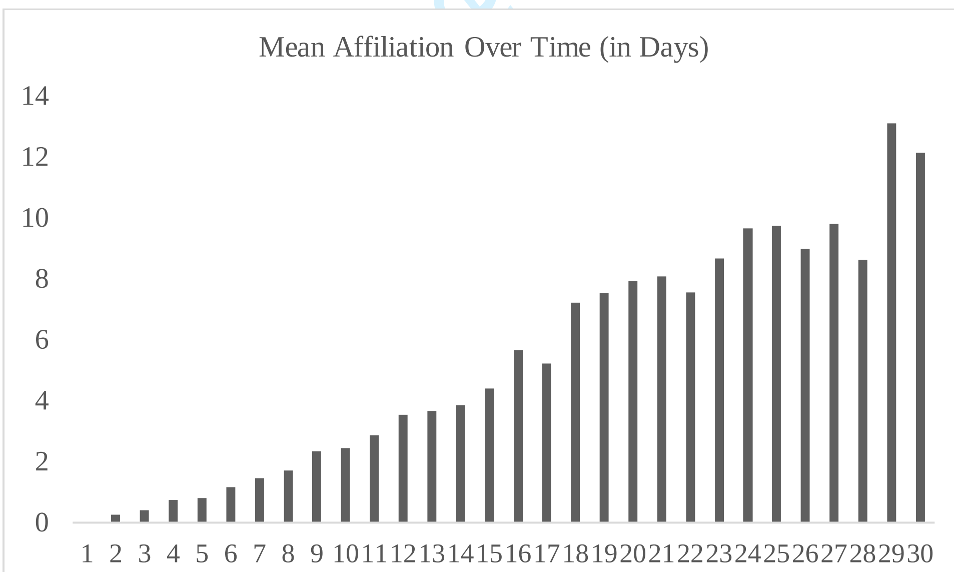


Figure W5. Mean of Ratio of Affiliation to Number of Backers, For Each Day of Funding Window

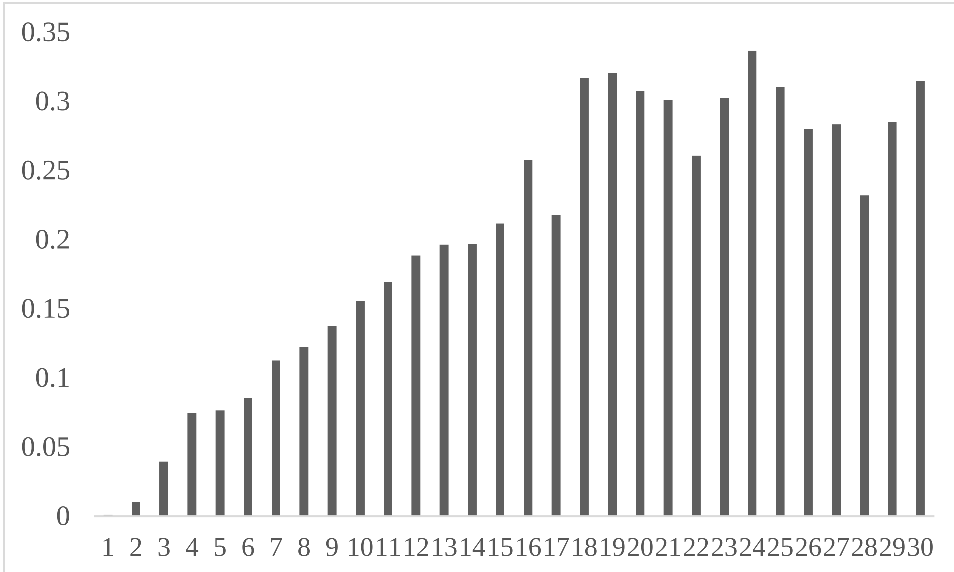


Figure W6. Bipartite Networks Showing Projects and Backers for Day 1 and Day 18 in the Data Collection Window (green nodes are projects and red nodes are backers)

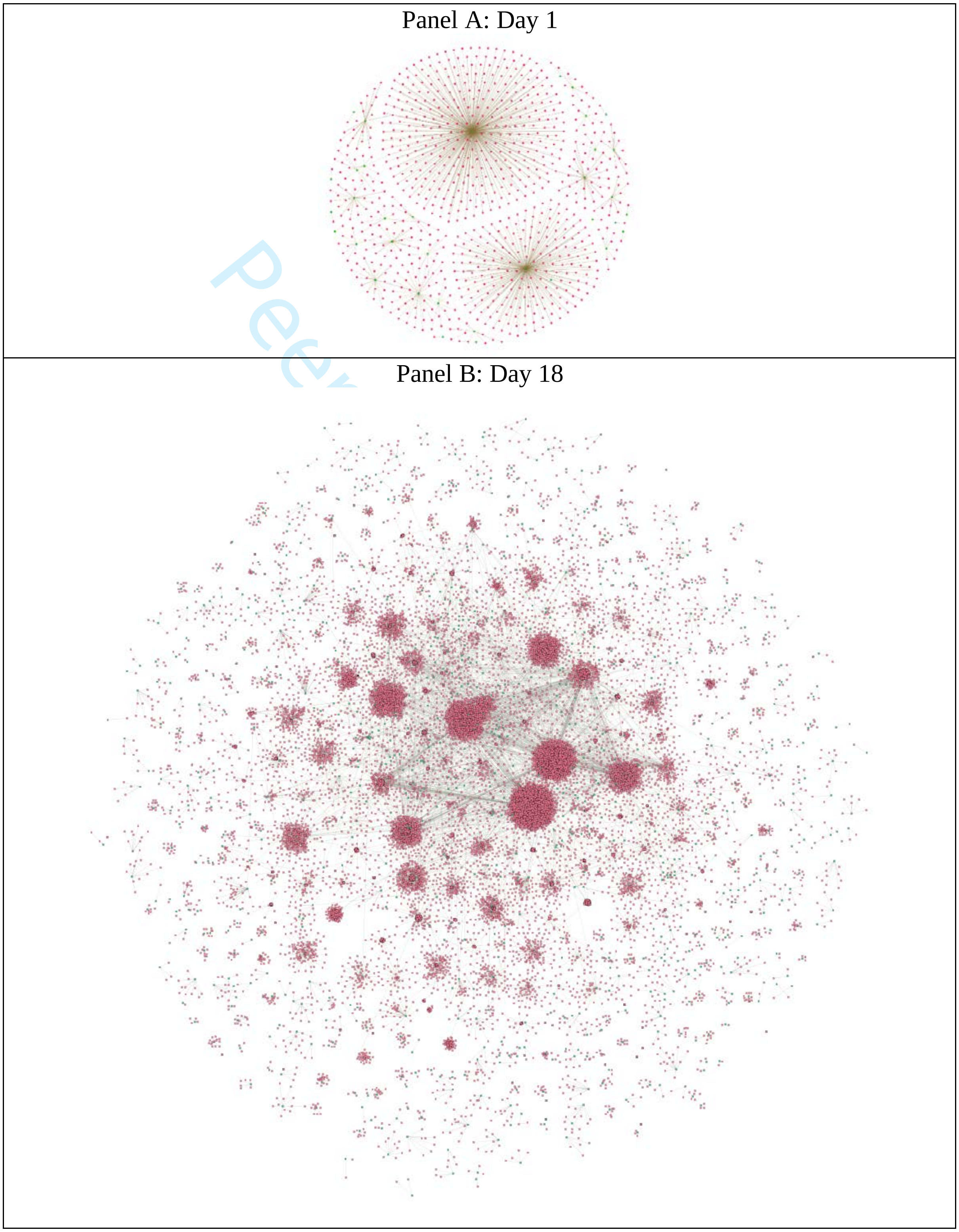
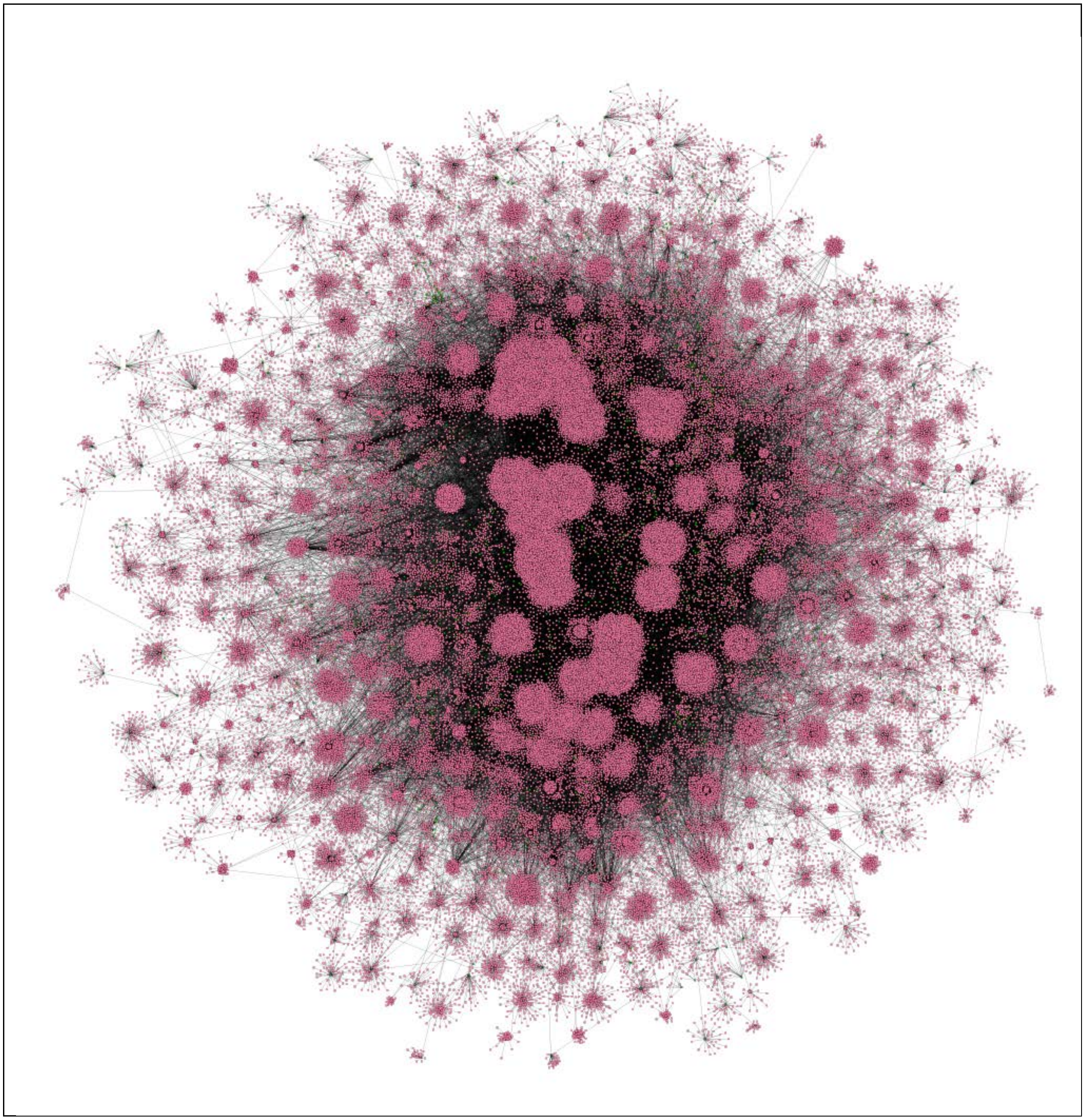


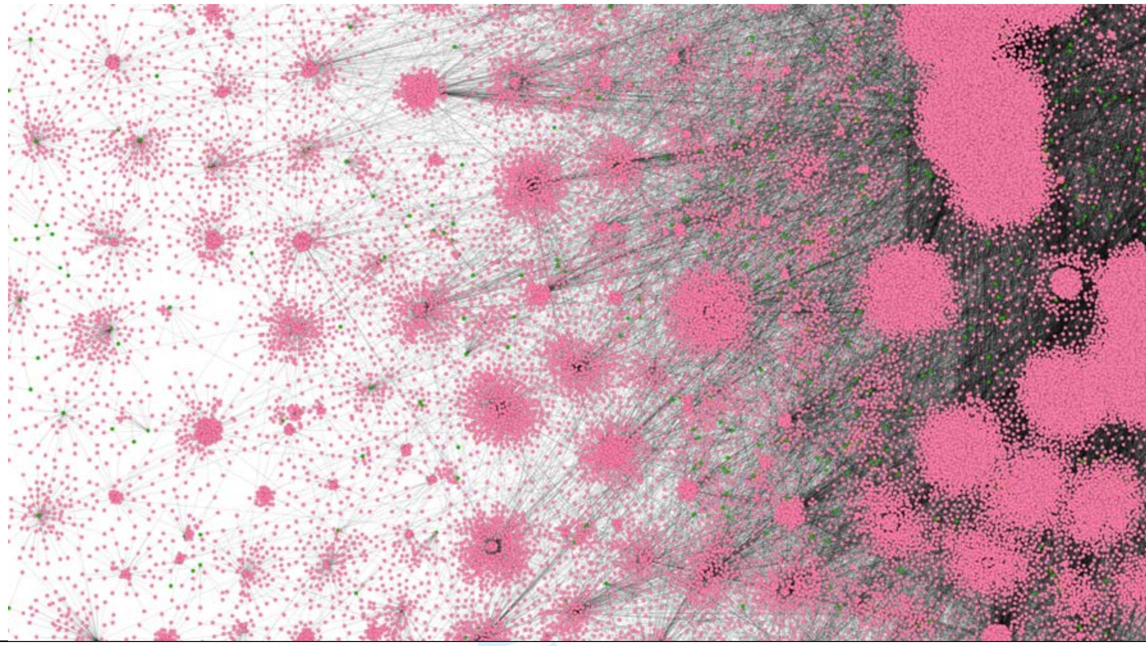
Figure W7. Bipartite Network for Day 37



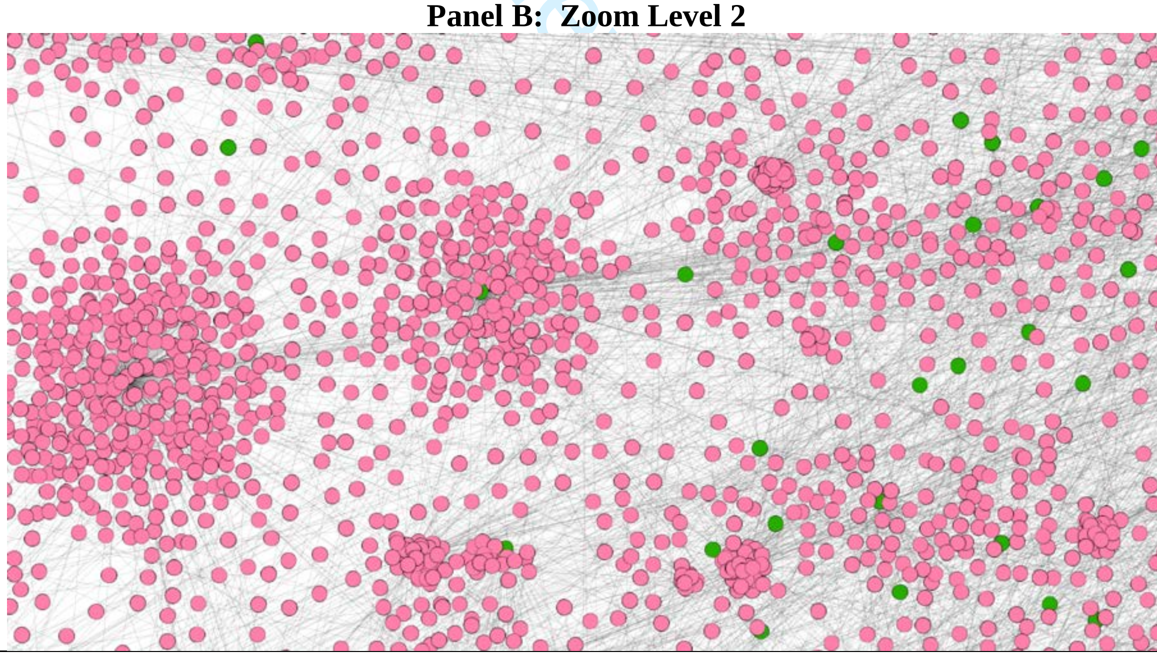
Notes: Pictorial representation of the network in the Kickstarter data sample at various visual granularity levels (see Figure A8). There are a total of 210,798 unique relationships in the sample among 1921 ideas and 170,989 backers. Pink nodes (visible in Panel A and Panel B in Figure A8) are backers, and green nodes are ideas. Small clusters show how a single idea attracts many backers. Higher resolution images are available from the authors. Images were generated using Gephi 0.6.

Figure W8. Bipartite Network on Day 37 at Different Levels of Magnification

Panel A: Zoom Level 1



Panel B: Zoom Level 2



Web Appendix F. Analysis of Indiegogo Data

Table W4. Coefficient Estimates of the Fixed Effects Regression Model of Daily Funding of Ideas on Indiegogo

Variable	**M1**	**M2**
Backer affiliation of idea *i* by day *t-1* ($Affil_{it-1}$)	-.29*** (.09)	-.27*** (.10)
Cumulative number of backers funding idea *I* by day *t-1* ($CumBackers_{it-1}$)	.11 (.06)	.17*** (.06)
Cumulative number of updates by creator of idea *i* by day *t-1* ($CumUpdates_{it-1}$)	1.19*** (.38)	1.21*** (.40)
Amount of funding of idea *i* (in $) in day *t-1*	.07*** (.03)	.07 (.04)
Proportion of funding goal of idea *i* achieved by day *t-1*	.36*** (.10)	.37*** (.10)
Proportion of funding duration of idea *i* completed by day *t-1*	.08 (.05)	.10*** (.05)
Fixed effects for each idea *i*	Yes	Yes
Fixed effects for each day *t*	Yes	Yes
Instrument	No	Yes

*** $p < .01$, ** $p < .05$, * $p < .10$

Web Appendix G. Analysis With Alternate Instrumental Variables

1. Latent Instrumental Variables

To demonstrate robustness to different instruments, we first employ latent instruments. This method yields consistent estimates, has reasonable power over a wide range of regressor-error correlations and is widely used in marketing (Ebbes et al. 2005, Rutz et al. 2012, Zhang and Godes 2018). We decompose each endogenous regressor into a systematic part uncorrelated with the funding equation's error term and a part potentially correlated with the error term. Thus, we specify,

$$\log\left(\text{Affil}_{it-1} + 0.001\right) = \pi \check{z}_{it-1} + \vartheta_{it-1} \quad \text{(W1)}$$

where $\check{z}_{it-1}$ is an unobserved (or latent) and discrete instrument of dimensionality and is independent of the error term by construction. π is a vector of *m* coefficients. To relax the assumption that backer affiliation is independent of the error term associated with the funding model, we allow for the error term associated with equation W1 correlated with the error term of the funding model (equation 1) as follows:

$$[\varepsilon_{it} \quad \vartheta_{it-1}] \sim \text{MVN}(0, \Sigma) \quad \text{(W2)}$$

Σ is an unrestricted covariance matrix. We specify the instrumental variable $\check{z}_{it-1}$, to follow a multinomial distribution with parameters (1, λ) where λ = $(\lambda_1, \lambda_2, \ldots \lambda_m)$ and $\sum_{r=1}^{m} \lambda_r = 1$. λ_r is the probability that the r^th^ latent instrument for the endogenous regressor is 1, i.e., the r^th^ element of the vector $\check{z}_{it-1}$ is one (and all other elements are zero). Identification requires the number of categories m to exceed one. Ebbes et al. (2005) discuss the properties of the LIV estimator, prove that it is identifiable through the likelihood and show that this method for mitigating endogeneity bias works over a wide range of regressor-error correlations and across several distributions of instruments. Estimates of λ_r close to zero or one are undesirable since they might indicate insufficient variation in the data to separate the endogenous regressor into discrete categories.

The LIV approach assumes that the measure of affiliation (the endogenous regressor) can be decomposed into two parts: an endogenous part (which is discrete) and an exogenous part. Although this assumption is empirically untestable, we note that our endogenous regressor is categorical. So, separating it into two parts, one of which is discrete, has conceptual appeal. The exogenous part could capture those co-backing relationships which trigger licensing, i.e., encourage backers to act in ways that differ from those of their affiliated backers. The endogenous part could capture the role of homophily or other unobserved characteristics that are common between affiliated backers – and which could potentially be correlated with the error term of the funding equation.

We use a Bayesian approach to estimate the model. We specify diffuse and uninformative prior distributions for model parameters and derive their posterior conditional distributions. Given the set of conditional distributions and priors, we draw recursively from the posterior distribution of the model parameters. We use data augmentation to draw the vector of instruments $\check{z}_{it-1}$, obviating the need to integrate it out. As the LIV estimator is robust to the number of categories (Ebbes et al. 2005), we choose the latent instrument to have two categories (i.e., m = 2).

Our estimate of the effect of affiliation using the LIV approach (posterior mean = -0.71, posterior SE = 0.08), falls between the OLS estimate (β = -0.04, $p < .01$), and the estimate using the observed instrument constructed from other categories (β = -0.86, $p < .01$). As Papies et al. (2017) suggest, it is reassuring that all estimates are directionally similar, and that the LIV estimate is not very different from other estimates.

As a robustness check, we estimate the LIV based model for different numbers of categories of instruments. For m = 2, 3 and 4, the LIV estimates are -0.74 ($p < .01$), -0.77 ($p < .01$) and -0.86 ($p < .01$) respectively. Similar estimates are reassuring. Very different estimates for different values of m could indicate an ill-defined instrument.

The LIV approach relies on the non-normality of the endogenous regressor. We test for non-normality by conducting the Shapiro-Wilk test and the Shapiro-Francia test. The null hypothesis is that $log\ (Affil_{it-1} + 0.001)$ is normally distributed. The Shapiro-Wilk test statistic and the Shapiro-Francia test statistic are 0.917 (Prob > z = 0.000) and 0.919 (Prob > z = 0.000) respectively. Both tests easily reject the null hypothesis.

Estimates of λ_r close to zero or one are undesirable since they might indicate insufficient variation in the data to separate the endogenous regressor into discrete categories. Our posterior estimates of λ_1 and λ_2 are 0.27 ($p < .01$) and 0.73 ($p < .019$) respectively, suggesting sufficient variation to separate the endogenous regressor.

2. Two Observed Instruments

Next, we use an observed instrument based on affiliation from another platform. For the model of Kickstarter data, we used the mean of affiliation (across ideas) in our Indiegogo data on the t-1th day from the commencement of funding of the ideas on Indiegogo as an instrument. This is a valid instrument if correlated with the endogenous variable but not with the error term in equation 1. The correlation between the endogenous variable (affiliation on Kickstarter) and the instrument (from Indiegogo) is 0.21, consistent with the view that affiliations are fundamental to social structure and evolve similarly across crowdfunding platforms. Indeed, network research has shown the commonality of such growth in various settings (e.g., Barabási and Albert 1999). The instrument from Indiegogo, in addition to being from a different platform, is less likely to affect the funding success of ideas in Kickstarter data as the instrument is from a future time-period and does not exist on day t of the Kickstarter data. It also varies over time, much like the endogenous variable.

Finally, we used an observed instrument based on co-backing behavior that varies both across time and over ideas. For this, we calculated Burt's measure of constraint (equation 2.4, p. 55 of Burt (1992)) of the idea i in time t as an instrument for affiliation. Constraint indicates structural holes in networks, a measure of unexploited opportunities to connect other nodes, and has been used in network research (Mallapragada et al. 2012). The constraint of a focal idea indicates the extent to which it acts as the only connecting point for backers to be affiliated with each other. If an idea's constraint is low, it means that backers had other opportunities to co-back through other ideas. Thus, conceptually, constraint is negatively related to affiliation. We expect greater affiliation among ideas with low constraint. The correlation between log of affiliation and log of constraint in our data is -0.39. Further, constraint satisfies the exclusion restriction. The focal idea's constraint measure in t-1 cannot affect funding in t because the constraint is only reflective of backers at t-1 and not backers who decide to fund on a focal day. We control for funding in day t-1 and employ fixed effects for each idea and day. So, the error term in equation 1 captures unobservables specific to the focal idea and day t. Constraint is also not an obvious metric, and we do not expect backers to consider it when making funding decisions. Thus, there is a limited conceptual argument to link constraint to funding directly. Thus, constraint satisfies both relevancy and exclusion criteria as an instrument. We find that results are consistent and robust across the various analyses.

References

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Web Appendix H. Alternate Models and Alternate Measures of Affiliation

1. Probit and Logit Models of Funding Success

Creators can avail of funds raised on Kickstarter only if the funding goal is reached. To assess the effect of affiliation on funding success, we estimate a Probit model, where the outcome is the funding success of idea *i* (1 if idea *i* received funding equal to its goal or more, and 0 otherwise). The key independent variable is the cumulative number of co-backings between all backers who funded the focal idea ($Affil_i = \sum_{t=1}^{T_i} Affil_{it}$). Control variables include the cumulative number of backers during the duration of funding, the cumulative number of updates, the cumulative number of positive, negative, and communal words in updates, the goal amount, the funding duration, the number of Facebook shares of the idea, means (over the funding window) of the three network measures, and the interaction terms from Equation 1. Again, we find a negative effect of affiliation (see table on the next page). The effect is robust to replacing the cumulative measure of affiliation with the mean level of affiliation across all days ($\sum_{t=1}^{T_i} Affil_{it}/T_i$). A negative effect of affiliation across datasets of different levels of aggregation demonstrates the robustness of our results[1]. Replacing the Probit with a Logit model yields similar results[2].

2. Tobit Model of Daily Funding

Since daily funding cannot take negative values, we specify a logarithmic transformation in equation 1. Another econometrically valid technique to deal with non-negativity in the funding data is to estimate a censored regression (or Tobit) model of daily funding.

On days that the distribution of backer preferences for the idea exceeds a threshold, the idea generates positive funding. In this model, y_{it} is determined by a normally distributed latent variable y_{it}^* such that $y_{it} = y_{it}^*$ if $y_{it}^* > 0$; else $y_{it} = 0$.

We estimate this model using the same covariates as equation 1, but without taking any logarithms. Since unconditional fixed effects are known to bias estimates of this model, we replace them with random effects, i.e., $\alpha_i \sim N(\alpha,\sigma^2)$. We again find a negative effect of affiliation; estimates appear later in this Appendix.

3. Effect of Alternate Measures of Affiliation

We assess the robustness of our findings to two alternative measures of affiliation. First, instead of using $Affil_{it-1}$, which is based solely on the number of co-backings between backers who fund on day *t-1*, and backers who fund before that day, we constructed a cumulative measure ($\sum_{t=1}^{t-1} Affil_{it-1}$), the sum (across days) of all co-backings between backers who fund on a specific day and backers who fund before that day. Second, we define $Affil_{it-1} = 1$ if there is at least one co-backing between a backer who funded idea *i* on day *t-1* and a backer who funded

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[1] Indiegogo allows creators to collect funds even if the funding goal is not met. Because of this, we restricted the analysis of "funding success" to the Kickstarter dataset.
[2] We also estimated a negative binomial model of the number of backers of idea *i* on day *t*, and found a negative effect of $Affil_{it-1}$ on the number of backers thus ruling out the explanation that prior affiliation leads to funding by more backers, but that these backers fund less. Details of this analysis are available on request.

idea *i* before that day; 0 otherwise. This is a binary measure that is less time consuming and cognitively less effortful for potential backers to compute than our original measure, and therefore theoretically appealing. We estimate the IV regression model described earlier with each of these measures and find negative coefficients for all of them. The coefficient of the cumulative measure of affiliation is -0.43 ($p < .01$), and that of the binary measure is -14.04 ($p < .01$).

4. Disaggregate model at the backer-idea-day level

We constructed a dataset at the backer-idea-day level and estimated a model of backer funding. We found a negative effect of backer affiliation on backer funding, after controlling for both observed and unobserved backer characteristics. First, we randomly sampled 95 ideas from the Kickstarter dataset of over 2,000 ideas. 11,189 backers have funded at least one of these ideas in our dataset. So we constructed a dataset at the backer-idea-day level, based on these 95 ideas and 11,189 backers, such that the binary dependent variable ($fund_{bit}$) is 1 if backer *b* funds idea *i* on day *t*, and 0 otherwise. This leads to a dataset of 7,216,905 observations, with $fund_{bit}$ taking zero values for 99.8% of all observations. Next, we estimated the following linear probability model, which utilizes the same covariates as the proposed model. y_{it-1} is the monetary funding received by an idea *i* on day *t*.

$$fund_{bit} = \alpha_i + \alpha_t + \alpha_b + \beta_1 Affil_{it-1} + \beta_2 CumBackers_{it-1} + \beta_3 CumUpdates_{it-1} + \beta_4 y_{it-1} + \beta_5 PropGoal_{it-1} + \beta_6 PropDuration_{it-1} + \beta_7 LastWeek_{it-1} + \beta_8 Network_{it-1} + \varepsilon_{it}$$

In addition to the time varying backer level covariate ($CumBackers_{it-1}$), this model controls for backer specific unobservables by incorporating backer fixed effects (α_b). The error term is assumed normally distributed. A non-linear model (such as logit) proved infeasible to estimate presumably due to the large number of fixed effects, and the sparseness of the dependent variable. Parameter estimates are consistent with those obtained from the models specified in the paper. In particular, the coefficient of affiliation is negative and significant (β = -6.85 X 10^{-5}, $p < .01$), and the coefficient of the cumulative number of backers (potentially capturing herding effects) is positive and significant (β = 0.000234, $p < .01$).

Table W5. Coefficient Estimates of the Probit and Logit Models of Funding Success

Variable	Probit Model with cumulative backer affiliation ($\sum_{t=1}^{T_i} Affil_{it}$)	Probit Model with mean daily backer affiliation ($\sum_{t=1}^{T_i} Affil_{it}/T_i$)	Logit Model with cumulative backer affiliation ($\sum_{t=1}^{T_i} Affil_{it}$)
Idea level measure of backer affiliation	-.029*** (.008)	-.279*** (.023)	-.064*** (.016)
Cumulative number of backers	.005*** (.0005)	.004*** (.001)	.012*** (.001)
Cumulative number of updates by creator	.005*** (.001)	.007*** (.001)	.009*** (.002)
Goal Amount (in $) ($10^3$)	-.026*** (.02)	-.039*** (.03)	-.060*** (.005)
Duration of funding (in days)	-.011*** (.004)	-.013*** (.003)	-.02*** (.01)
Closeness centrality of idea *i* (mean over days)	0.97 (1.97)	1.17 (2.31)	1.10 (3.43)
Betweenness centrality of idea *i* (mean over days)	-.005 (.006)	-.006 (.006)	-.018 (.011)
Eigenvector centrality of idea *i* (mean over days)	.88 (2.22)	1.20 (2.13)	1.38 (3.68)
Number of communal words in all updates by creator of idea *i* ($CommunalUpdates_i$)	.58*** (.11)	.59*** (.12)	1.21*** (.23)
Number of Facebook shares of idea *i* ($FBShares_i$)	.09*** (.01)	.09*** (.02)	.14*** (.01)
$Affil_i$ X $CommunalUpdates_i$	-.003*** (.001)	-.003*** (.001)	-.007*** (.002)
$Affil_i$ X $FBShares_i$	-.0004*** (.0001)	-.0003*** (.0001)	-.007*** (.0002)

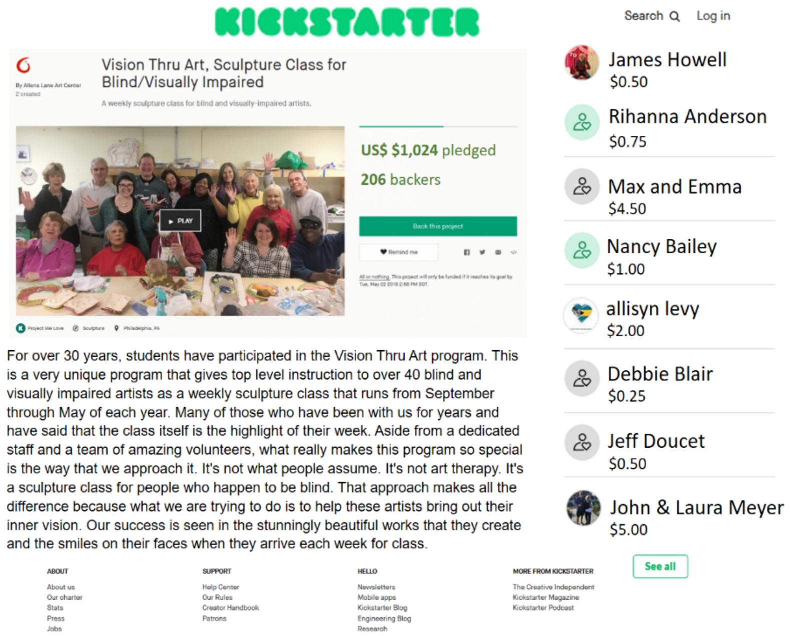
*** $p < .01$, ** $p < .05$, * $p < .10$; All models include category specific fixed effects.

Web Appendix I. Controlled Experiments

In all of our studies, we included an open-ended question asking participants about their funding decision. Participants were removed if they noted that they had a personal connection to the idea's specific product or cause. In experiment 1, four participants were removed who indicated 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. No participants mentioned connection to the other idea's cause. In experiments 2 and 3, no personal connections were disclosed – perhaps unsurprising, given the ideas included in these studies.

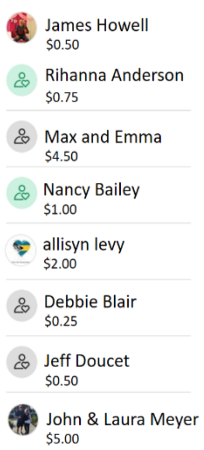
Experiment 1: Additional Details

First, participants saw the following web page for the first idea seeking funding and asked if they would like to fund:

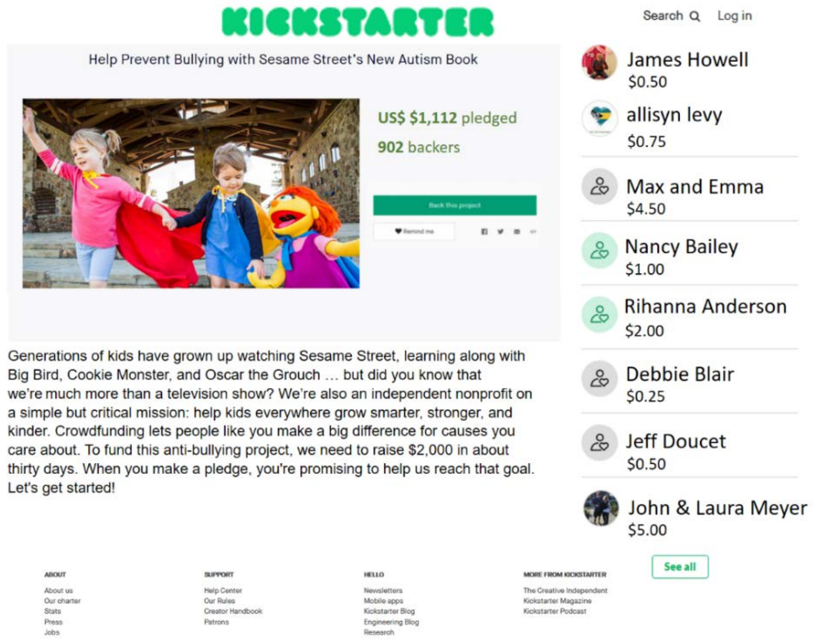


All participants who opted to fund then read:

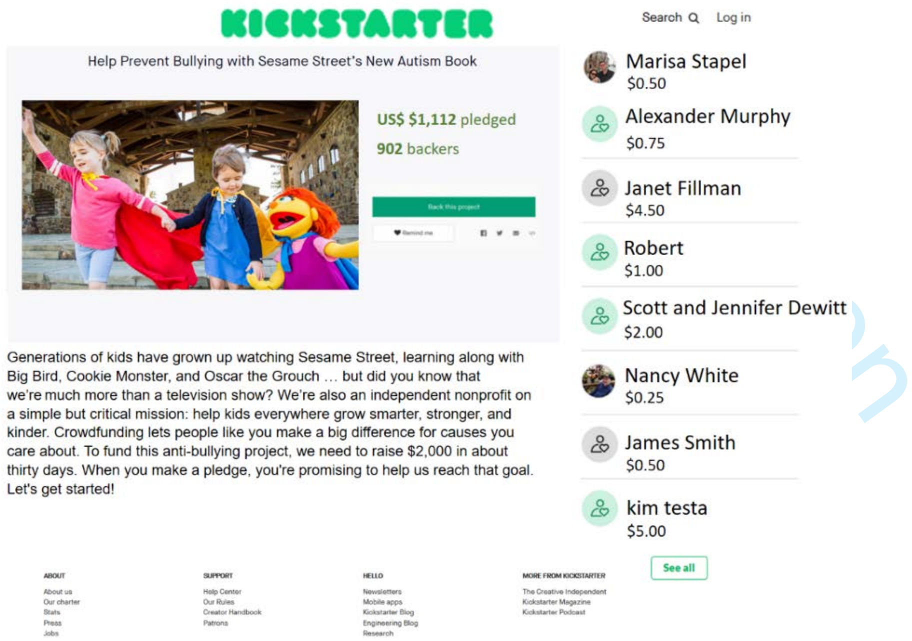
As a reminder, you previously funded Vision Through the Arts, which already has received pledges for over $1,000 from 206 backers <u>including the following</u>:



Participants were then exposed to the affiliation manipulation. Those in the *high affiliation* condition saw the following web page, which includes high overlap in backers who funded the first idea:



Those in the *control affiliation* condition saw the following web page, which includes no overlap in backers who funded the first idea:

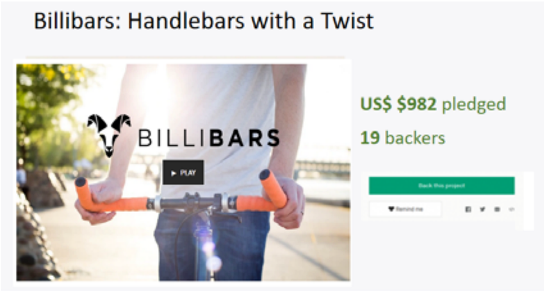


This experiment included a manipulation check to confirm the effectiveness of the affiliation manipulation. Participants across both conditions were asked, "Of the people funding Vision Thru Art, how many of them are also funding the Sesame Street Autism Project" (None at all, very few, a moderate amount, very many, all of them). As expected, those in the high affiliation condition (3.64) perceived more than those in the control affiliation condition (3.23), ($F(1, 100) = 3.13$, $p = .08$).

Experiment 2: Additional Details

First, participants were told to “Imagine for a moment that you have $50 to fund one of the following projects. Which one would you choose? (You can only choose one.)”

They were then shown screen shots for four ideas from which to choose:

1.


Billibars are detachable handlebars that reduce a bike's width by over 45% and create a space-saving mount to hold the bike.

Another cool feature of Billibars is our unique, patented wall mount that utilizes the removed handlebars to hold your bike securely and closely to the wall.

2.


We are starting a fully transparent, sustainably sourced meat company!

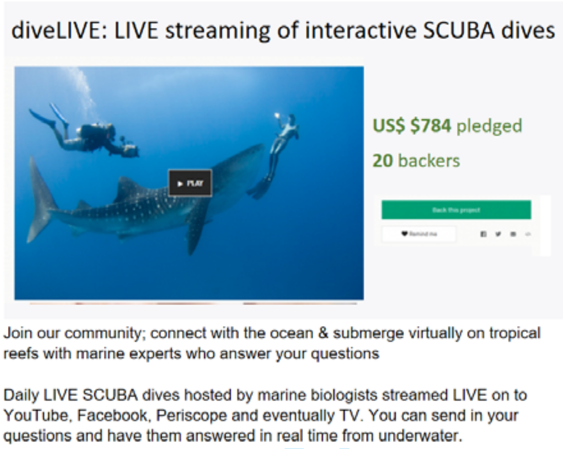
Made fresh from the whole animals we receive each week, our sausages are all made fresh in our shop. We offer over 50 different kinds of sausage, but the list below may not reflect what we have in stock each day.

3.


SunPort is about accelerating America’s shift to solar energy, by letting everyone participate in crowdsourcing demand for it. What better place to do that than Kickstarter?

We all know the world is going solar. The issue is not if, but when. We need it now, so the key question is "how?" How do we get it done?

4.



Next, all participants read about an idea seeking funding:

Sealand Eco Collection is a selection of bags & accessories to perfectly match your urban outdoor lifestyle. The entire collection is produced from Recover®, an environmentally responsible fabric, made from a high quality blend of upcycled Cotton and post-consumer recycled PET bottles.

This collection boasts an environmental consciousness, long lasting quality and multi-functionality.

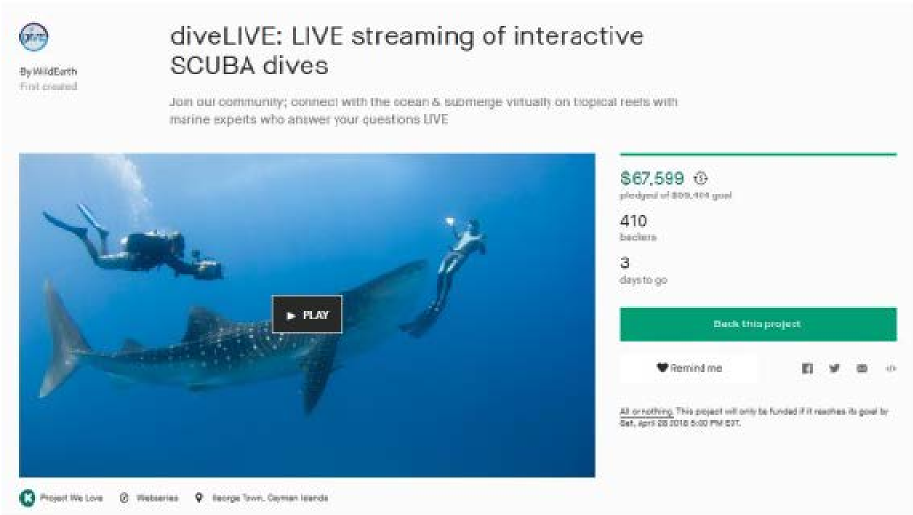
Participants in the *high affiliation* condition read: "A **large number (> 50%) of the people funding [project chosen], the first project you funded, are currently funding this project."**

Participants in the *control affiliation* condition did not receive any additional information regarding the overlap in funding between the two ideas.

We conducted a pretest on Amazon Turk with 151 North American residents (M_{Age} = 36.73 years, 51.7% women; 31.8% of whom have previously funded an idea on an online crowdfunding platform) to confirm the effectiveness of the affiliation manipulation. Participants saw the same ideas and manipulations and were asked: "Of the people funding [project chosen], how many of them are also funding Sealand Eco?" (None at all, very few, a moderate amount, very many, all of them). As expected, those in the high affiliation condition (3.53) perceived more than those in the control affiliation condition (2.99), ($F(1, 149) = 27.33$, $p < .01$).

Experiment 3: Additional Details

All participants read about Sealand Eco as in the previous experiment. Next, all participants read about diveLIVE, a second idea seeking funding:



Those in the *more communal* condition read the following project description:

Let's learn about the oceans

This is why we want to launch diveLIVE, a pioneering LIVE virtual diving experience. We believe that if we can get people to understand the oceans, they will all be encouraged to think about them more often.

Our mission is to make history because the ability for divers to talk underwater while streaming LIVE video to the internet was limited. Until now that is, as we have developed technology and systems that will enable exactly this.

Through diveLIVE, we now want to do the same for the oceans. We aim to keep doing this indefinitely. diveLIVE is not a once-off or short-term endeavor but set up to be a long-term and sustainable way of researching the oceans.

Those in the *less communal* condition read the following project description:

This product uses technology to take videos of the oceans

This is why we want to launch diveLIVE, a pioneering LIVE virtual diving experience. We believe that if we can get people to use this platform, they will all be encouraged invest in this business opportunity.

By investing in this platform, our technology will be making history because the ability for divers to talk underwater while streaming LIVE video to the internet was limited. Until now that is, as we have develop technology that will enable us to do exactly this.

Through diveLIVE, we now want to do the same for our investors. We aim to keep growing indefinitely. diveLIVE is not a once-off or short-term endeavor but set up to be a long-term and sustainable business venture.

Affiliation was manipulated just as in experiment 2. Participants in the *high affiliation* condition read for each: "A l**arge number (> 50%) of the people funding Sealand Eco, the first project you funded, are currently funding this project."**

Participants in the *control affiliation* condition did not receive any additional information regarding the overlap in funding between the two ideas.

Figure W9. Effect of Affiliation and Idea Description on Funding (Experiment 3)