Early Backers' Social and Geographic Influences on the Success of Crowdfunding

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Abstract:

Purpose—While crowdfunding provides a novel method for entrepreneurs and startups to raise funding from consumers, a high percentage of crowdfunding projects fail to achieve their funding goals. This study investigates the impact of early backers on crowdfunding success (i.e., reaching funding goals) by considering their social and geographic peer influences.

Design/methodology/approach—I constructed a social network and a geographic network of crowdfunding backers based on a dataset from Kickstarter.com and used closeness centrality to quantify the network positions of early backers.

Findings—For project categories with low completion uncertainty, early backers who were socially closer to their peers led to a higher chance of success. However, such an impact declines for projects with higher uncertainty. On the other hand, for project categories with high completion uncertainty, early backers who were geographically closer to their peers led to a higher chance of success. Still, such an impact declines for projects with lower uncertainty.

Originality/value—This paper contributes to the literature by investigating the peer influence between socially and geographically related consumers on a crowdfunding platform. The findings provide managerial implications for crowdfunding project creators to target the right crowd.

1. Introduction

Crowdfunding through online platforms has become a vital practice for entrepreneurs and startups to seek financial support for their innovations (Theerthaana and Manohar 2021). In the face of barriers to traditional funding sources, such as banks and venture capital, financial support can now be raised from online communities of consumer investors, viz. backers or crowdfunders (Economist 2010; Kuppuswamy and Bayus 2017). There are different types of crowdfunding, including reward, patronage, lending, and equity (Mollick 2014). This study focuses on reward-based crowdfunding, in which consumers are involved in financing products that are not yet available for purchase and can collectively determine whether a product will be developed and delivered (Zvilichovsky *et al.* 2017). Reward-based crowdfunding exists as a great example of how electronic platforms and interactive technologies transform consumer experience and behavior from classical consumer purchasing and creates new research opportunities (Bender *et al.* 2019; Wang 2021). On one of the largest reward-based crowdfunding platforms—Kickstarter, a total of 16 million backers have invested more than $4.5 billion and funded more than 169,874 projects (kickstarter.com 2019).

Despite the growing importance of crowdfunding to innovations, the percentage of crowdfunding projects that have achieved their funding goals (i.e., success rate) has been remarkably low. For example, Kickstarter reported an average success rate of 37.35% in 2019, with technology projects having the lowest success rate, at 20.55%. This situation is exacerbated by the "all or nothing" policy implemented by major crowdfunding platforms, in which projects that fail to reach funding goals do not receive any contributions from backers. Hence, how to reach their funding goals within the preset funding period becomes a crucial question for entrepreneurs and startups to ensure crowdfunding success.

Previous studies find that a critical factor in crowdfunding success is the early momentum (i.e., the funding that a crowdfunding project can attract during its early stage) (Colombo *et al.* 2015; Zhang and Liu 2012). A well-known "Kickstarter effect" suggests that crowdfunding projects are more likely to succeed (i.e., achieve their target goal) if they can reach at least 30% of their funding goal during the early stage of crowdfunding (Kuppuswamy and Bayus 2017). On reward-based crowdfunding platforms, two types of backer-related information are generally available to consumer investors: (1) funds that existing backers have contributed (e.g., the cumulative amount of funds raised to date) and (2) information about current backers (e.g., the number of existing backers, their online identity, past funding activities, and geographic locations). Crowdfunders' funding information and their social and geographic information create conditions for observational learning and social interaction among consumer investors.

In recent years, a number of studies discovered the *herding effect* in crowdfunding, showing that early backers' influence indeed exists (Chan *et al.* 2020; Xiao *et al.* 2021; Tian *et al.* 2021). Lin and Viswanathan (2015) also found evidence of *home bias* existing in online crowdfunding, i.e., backers' tendency to support projects in the same geographic area rather than outside. Four studies focused on the social and geographic relationship between existing funders and project creators and their impact on crowdfunding success (Mollick 2014; Agrawal *et al.* 2015; Kang *et al.* 2017; Simon *et al.* 2019). However, the impacts of early backers are underexplored from the perspective of their relationships with other backers.

In this paper, I examined the impact of early backers on the success of crowdfunding with data collected from Kickstarter, including 191 projects and 18,715 backers. The empirical analysis revealed three important results. First, I found the evidence of early backers' impacts on crowdfunding success, implying that early backers indeed influenced the followers' funding decisions. Second, the impacts of early backers' social and geographic closeness centralities vary in opposite directions with the uncertainty of project completion. As completion uncertainty increases, early backers became less influential when they were socially close to other crowdfunders but more influential when they were geographically close to other crowdfunders. Third, we empirically found that early backers could exert not only a positive but a negative influence on the success of crowdfunding.

This study contributes to the literature on interactive marketing, crowdfunding, and social influence. First, it draws attention to the changes in consumer experience and behavior as a result of the development of interactive technologies and platform ecosystems. Second, the current study is among the first to simultaneously investigate the impacts of social and geographic distance between consumer investors on crowdfunding success. Third, I identified an important moderator—the uncertainty of project completion—in early backers' social and geographic influences. Lastly, this study demonstrates evidence of possible negative social influences, encouraging future research on a more comprehensive understanding of social influence.

2. Theoretical Background and Development

To analyze the impact of early backers' social and geographic influences, I first construct a social network and a geographic network of crowdfunders, which allows us to gauge backers' social and geographic positions.

2.1. Social and Geographic Networks of Crowdfunders

Social Network of Crowdfunders. I define the social network of crowdfunders by adopting a two-mode affiliation network analysis (Grewal *et al.* 2006; Ransbotham *et al.* 2012). A two-mode affiliation social network typically consists of two key elements: a set of actors and a collection of events (Faust 1997). In crowdfunding, the actors are the backers, and the events are the projects they have funded previously. A pair of backers are defined as socially connected when they have previously funded the same project(s). Based on crowdfunders' funding history, their social network can be constructed.

To illustrate, I present a sub-network of 33 backers extracted from a project in the data (shown in Figure 1), where early backers are labeled in red, and their followers are labeled in green. In this sub-network, early backer J. R. has connections with 13 other backers, indicating that backer J. R. has previously funded at least one project in common with each of them. The thickness of a line between two backers represents the strength of the connection, determined by the number of shared projects between two backers. In Figure 1, J. R. connects to K. O. strongly, with ten shared projects.

[Insert Figure 1 here]

This social network captures the embedded social interactions among crowdfunders who have funding experiences in a crowdfunding community. A stronger connection between a pair of crowdfunders in such a network represents a higher level of shared experience, knowledge, or interest in their funding choices. According to the social network literature, such an embedded social network measures the quantity and quality of possible online social interactions among crowdfunders and reflects the social capital of crowdfunders. Social capital is often defined as "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (Nahapiet and Ghoshal 1998, p. 243). The social capital of early backers can affect other potential backers and, eventually, the success of crowdfunding projects.

Geographic Network of Crowdfunders. To capture influences due to geographic locations, I also define a geographic network of crowdfunders on a crowdfunding platform based on the latitude and longitude coordinates of their locations (i.e., city, state, and country). After constructing these two networks, I can quantify a crowdfunder's social and geographic relationships with others in the social and geographic networks.

Quantifying the Social and Geographic Position of Early Backers. To do so, I adopt the concept of closeness centrality from the network analysis literature. Closeness centrality captures the degree of an early backer's centrality in a network based on the shortest distances from the early backer to all other backers (Bavelas 1950; Beauchamp 1965; Sabidussi 1966; de Nooy *et al.* 2005; Stephen and Toubia 2010; Hansen *et al.* 2011). The social closeness centrality of a backer b_i ($BSCC_{b_i}$) is denoted mathematically as $\frac{N-1}{\sum_{j=1, j\neq i}^{N-1} d_s(b_i, b_j)}$, where $d_s(b_i, b_j)$ is the social distance between the backer b_i and another backer b_j. The distance is measured by the sum of weights of the dyadic connections on the shortest path between two vertices in a network. In the social network of backers, I define the weight of a dyadic connection between backers as the reciprocal of the number of projects they both invested in, since the more common activities two backers share, the closer their distance should be. According to the definition, a higher social closeness centrality value of an early backer indicates that she is, on average, socially closer to others in the network.

To provide a consistent measure of the geographic relationship, I also develop the geographic closeness centrality of a backer b_i ($BGCC_{b_i}$) to capture the degree of an early backer's position in the geographic network. Mathematically, *BGCC* is denoted as $\frac{N-1}{\sum_{j=1, j\neq i}^{N-1} d_g(b_i, b_j)}$, where $d_g(b_i, b_j)$ is the geographic distance between the backer b_i and all other crowdfunders b_j. This distance can be calculated by the coordinates of backers' locations. Similarly, a higher geographic closeness centrality score of an early backer indicates that she is, on average, geographically closer to other backers in the network.

2.2. Early Backers' Impact on Crowdfunding

In the sociology and marketing literature, researchers have theoretically examined and empirically documented how people influence others within a social network (e.g., Festinger *et al.* 1948; Uzzi and Spiro 2005; Childers and Rao 1992; Goel and Goldstein 2013; Zhao and Xie 2011). In general, an individual has a greater impact on her socially close peers than on distant ones (e.g., Banerjee 1992; Bikhchandani *et al.* 1992; Zhao and Xie 2011). Two mechanisms generate social influences among socially close people: informational social influences and normative social influences (e.g., Deutsch and Gerard 1955; Burnkrant and Cousineau 1975). Informational social influence refers to the influence "to accept information obtained from another as evidence about the reality" (Deutsch and Gerard 1955), whereas normative social influence refers to the influence generated from people's tendency to conform to socially related others (Deutsch and Gerard 1955; Burnkrant and Cousineau 1975). Literature suggests that normative social influences can happen through either the process of compliance or identification (Kelley 1967; Burnkrant and Cousineau 1975). Overall, because people can quickly disseminate information to socially close others, and because people can easily observe the behavior of socially close others, an individual in the center of a social network can impose stronger influences.

An increasing number of studies in marketing, economics, and sociology have also investigated how people influence their geographically close peers, i.e., neighborhood effects (e.g., Bala and Goyal 1998; Bell and Song 2007; Conley and Udry 2010; Choi *et al.* 2010; Duflo and Saez 2003; Lee and Bell 2013; Sorensen 2006). In general, people are more likely to be influenced in their offline and online consumption, investment, and purchase decisions when they are geographically close. The underlying mechanisms driving the observed neighborhood effects can also be informational or attributable to social conformity (Van den Bulte and Lilien 2001; Amaldoss and Jain 2005; Lee and Bell 2013). Furthermore, the literature on venture capital and stock investment has demonstrated that investors might select startups or stocks to invest in due to their close location, exhibiting a so-called home bias (e.g., Baker and Nofsinger 2002; Coval and Moskowitz 1999; Lai and Teo 2008; Lin and Viswanathan 2016; Strong and Xu 2003). For example, Lai and Teo (2008) show that investors consistently concentrate their investments in equities from their home country, despite the potential benefits of international equity diversification. Coval and Moskowitz (1999) point out that the preference for investing close to home also applies to portfolios of domestic stocks. U.S. investment managers also exhibit a strong preference for locally headquartered firms (Huberman 2001).

In crowdfunding, I expect similar peer influences of early backers to exist in their social and geographic networks. Early backers can influence their peers through direct social interactions such as information sharing on social media (e.g., Facebook, Twitter), commenting on each other on the crowdfunding platform, or through observational learning (Colombo *et al.* 2015). Information sharing may create informational social influence, while observational learning may generate normative social influences. Observational learning can be an essential mechanism for social influences when crowdfunders do not engage in any direct communications. Because there can be as many as thousands of live projects on a crowdfunding platform every day, observing the funding choices of socially close others can make those choices more salient than the alternatives (i.e., the so-called saliency effect) (Cai *et al.* 2009). Thus, if an early backer has a more central position in the social network, he can impose a more substantial influence on his peer. In a similar fashion, a crowdfunder could imitate early backers who are located closely due to the saliency effect or perceived familiarity and trustworthiness when the crowdfunder identifies himself as associated with the early backers and, hence, becomes more willing to conform to their choices.

2.3. The Moderating Role of Project Completion Uncertainty

The sources of information asymmetry that buyers face in online markets include seller uncertainty and product uncertainty (e.g., Ghose 2009; Dimoka *et al.* 2012). Both are relevant to consumer investors' decision-making in crowdfunding. Product developments of crowdfunding projects are mostly in the early stages and are inherently risky (Moysidou and Hausberg 2020). A primary concern to consumer investors is whether project creators can deliver their projects on time, as promised when seeking funding from the crowd (Schiavone 2017). As such, the completion uncertainty is exceptionally high for projects that adopt novel technologies or complex production processes (Kuppuswamy and Bayus 2017). Because many project creators have little experience in building a product and dealing with logistics and suppliers, there can be a significant chance of project failure (Agrawal *et al.* 2014). A study found that among 247 successful projects in the design and technology categories on Kickstarter (i.e., those that successfully raised their funding goal and promised to deliver products), a vast majority of them (approximately 75%) delayed, and some (approximately 4%) did not deliver at all (Mollick 2014). Crowdfunding literature has also recognized the crucial impact of project completion uncertainty on crowdfunding's success but only focused on the negative main effect of uncertainty (e.g., Belleflamme *et al.* 2014; Ahlers *et al.* 2015).

Moderating Effect of Uncertainty in Social Influence. As the project completion uncertainty increases, crowdfunders may have a more substantial need to seek new information or to observe the behavior of backers possessing new information to make better investment decisions (FeldmanHall and Shenhav 2019). However, an early backer located in the center of the embedded social network may not possess any different information than his socially close peers (Hansen 1999). As the social network literature pointed out, an information disadvantage exists in a highly central and close-distance network (Granovetter 1973; Coleman 1988; Baer 2010). Granovetter (1973), in his theory of the strength of weak ties, suggests that more new information is likely to flow between individuals through weak ties rather than strong ties. Fundamentally speaking, a high social closeness centrality implies that the backer invests in a large number of projects, and the backer invests in popular projects together with others. This means that 1. he is more resourceful financially and, thus, more capable of taking risks in investments than average consumer investors; and 2. he tends to make similar judgments on projects as lots of crowdfunders do, and thus, is unlikely to possess any extra information for assessing a more uncertain project. Therefore, an early backer's investment decision with high closeness centrality will have less reference value when project uncertainty is higher. In other words, the positive impact of closeness centrality will decrease when the completion uncertainty of a crowdfunding project increases.

H1: For early backers with a high social closeness centrality, their positive impacts on the success of crowdfunding projects become weaker as the project completion uncertainty increases.

Moderating Effect of Uncertainty in Geographic Influence. Backers with little or no crowdfunding experience are more likely to be hesitant to invest in high-uncertainty projects than in low-uncertainty ones (Belleflamme *et al.* 2014). However, an observation of the investments from geographically close peers can generate a sense of familiarity and trust that helps reduce the perceived uncertainty even when the backer's online social connection is absent (Meyners *et al.* 2017). Moreover, by definition, a backer's geographic network also reflects the density of the population showing interest in crowdfunding investment around his place of residence. In particular, a backer with higher geographic closeness centrality is more likely to encounter another (potential) crowdfunder in offline interactions. When the completion uncertainty is higher, a project will, in general, face more challenges in raising the funding successfully. Nevertheless, existing backers of the project will have had strong interests in the idea proposed in the project and had the capability and willingness to take risks when pledging to the project. Given the higher chance of failure for the project they have invested in, there will be more incentives for the existing backers to exploit their offline social capitals to help the project succeed by disseminating the availability and value of the project among their offline peers. Therefore, as project uncertainty increases, the positive impact of geographic closeness centrality will be even stronger.

H2: For early backers with a high geographic closeness centrality, their positive impacts on the success of crowdfunding projects become stronger as the project completion uncertainty of increases.

3. Empirical Analysis

3.1. Model

I adopt a logistic model to examine the geographic and social impacts of early backers on the probability of project success. Specifically, I model the probability of project *p*'s success as a logit function given by

$$\Pr(\text{Success}_p = 1) = \frac{\exp(X_{ip}\vec{\beta})}{1+\exp(X_{ip}\vec{\beta})}, \tag{1}$$

where X_{ip} denotes a vector of explanatory variables for project p with early backer i, including the early backer's geographic and social closeness centrality as well as the project's and the project creator's characteristics. $\vec{\beta}$ denotes the vector of coefficients to be estimated. The empirical specification for $X_{ij}\vec{\beta}$ is given by

$$\begin{aligned} X_{ip}\vec{\beta} = \beta_0 &+ \beta_1 EBSCC_{ip} + \beta_2 EBGCC_{ip} + \beta_3 EBSCC_{ip} \times Uncertainty_p + \beta_4 EBGCC_{ip} \times Uncertainty_p \\ &+ \beta_5 EBSCC_{ip} \times EBGCC_{ip} + \beta_6 Uncertainty_p + \beta_7 Distance_{ip} + \beta_8 Goal_p + \beta_9 FDP_p \\ &+ \beta_{10} PLGDW1_p + \beta_{11} AVGPLGDW1_p + \beta_{12} PBGCC_p + \beta_{13} Failed_p + \beta_{14} Succeeded_p \\ &+ \beta_{15} Backed_p + \beta_{16} FBF_p, \end{aligned} \tag{2}$$

where $EBSCC_{ip}$ and $EBGCC_{ip}$ denote the project p's early backer i's social closeness centrality in the online social network and geographic closeness centrality in the offline geographic network, respectively. $Uncertainty_p$ measures the completion uncertainty of the project category to which project p belongs. The interaction terms of $EBSCC_{ip} \times Uncertainty_p$ and $EBGCC_{ip} \times Uncertainty_p$ capture the moderating effects of $Uncertainty_p$. I incorporate five additional project-specific variables: $Goal_p$, FDP_p, $PLGDW1_p$, $AVGPLGDW1_p$ and $PBGCC_p$. $Goal_p$ denotes the amount of funding that the project creator aims to raise for project p. FDP_p denotes the length of the funding period in days. $PLGDW1_p$ and $AVGPLGDW1_p$ denote the total and average amounts of funding that are pledged during the first week of project p's funding period, respectively. $PBGCC_p$ denotes the project creator's geographic closeness centrality to all backers, which is measured by the inverse of the average distance from the project to each backer. To control the experience and characteristics of the project p's creator, I include three variables – $Failed_j$, $Succeeded_j$, and $Backed_j$ – which capture the number of the creator's projects that have failed and succeeded and the number of projects that the creator has backed in the past, respectively. I also include the number of Facebook friends that the project creator has in the variable FBF_j.

3.2. Data

The data were collected from one of the most popular crowdfunding websites, Kickstarter. I started the data collection on Feb. 10, 2014 and recorded all newly launched projects on Feb. 10 and Feb. 11, 2014. Then, I tracked each project weekly and documented the number of new backers and their funding pledged each week until the funding period ended or was canceled by the creator. Among the 199 projects launched on Feb. 10 and Feb. 11, 2014, eight were canceled by their creators during the funding periods and were therefore excluded from the data due to a lack of information on why the creators abandoned their projects. Overall, I collected information on 191 projects and 18,715 crowdfunders who funded at least one of the 191 projects over nine weeks.

The dataset consists of project-level variables and backer-level variables. At the project level, I recorded each project's location (i.e., city, state, and country), category, funding goal, and information about the creator, such as the number of projects he had created, how many of the projects had succeeded, and how many other projects he had backed before the present project. The projects' funding periods are set by the creators and vary from 10 to 60 days, with an average of 32 days. During the funding period, I recorded the number of new backers and funding pledged each week. When the project ended, I recorded whether the project had achieved its funding goal (i.e., succeeded or not). Of the 191 projects in the data, 46.6% succeeded by the end of the funding period. The average funding pledged for successful projects is $15,960.78, whereas the average funding pledged for all 191 projects is $8,690.77.

At the backer level, I collected all available geographic locations of backers (i.e., city, state, and country) and their backing history, including the projects they backed previously.[1] For each project in the data, I considered backers who pledged during the first week of the project's funding period as early backers. Among 18,715 backers across all projects, there are 6,986 early backers. I also used an alternative criterion – the 30% of funding goal achieved to classify crowdfunders as early backers and yielded consistent results.[2] Of the 191 projects, 22 received zero funding pledges in the first week. Only one of these 22 projects succeeded after the funding period ended, indicating the important impact of early backers. Moreover, none of the 191 projects had achieved their funding goals in the first week of crowdfunding, indicating the importance of following backers.

To study the social and geographic impact of early backers, I first built the geographic and social networks of all crowdfunders in the data. To define the social connection between a pair of crowdfunders, I tracked back all of the projects that each backer in the sample had funded in the past and constructed the social network accordingly. Based on the definition of the embedded social network described earlier, I then identified 1,048,576 social connections among these 18,715 crowdfunders and constructed their social network. I constructed the geographic network of the crowdfunders according to the latitude and longitude of the crowdfunders' home city. I obtained the latitude and longitude coordinates from GeoLite City, a geographic coordinate database[3]. Based on the social and geographic network, I calculated *EBGCC* and *EBSCC* for each early backer in the data. To control for the impact of project creators' geographic locations,

[1] Kickstarter changed the design of its website in 2015. Since then, individual backers' geographic location (i.e., city, state, and country) and backing history are no longer publicly available. Instead, aggregated geographic information and funding information of backers are shown on the project's webpage.
[2] The empirical results with the alternative classification of early backers are available upon request.
[3] http://dev.maxmind.com/geoip/legacy/geolite

I also calculated the closeness centrality of project creators in their geographic network based on the same definition and denoted as *PBGCC*.

I measured the completion uncertainty of 13 project categories using a survey of 100 participants on Amazon Mechanical Turk. I provided the description of each project category and measured uncertainty on a 3-item scale developed based on the past literature (Tatikonda and Montoya-Weiss 2001, Oh and Rhee 2008). The three items include: (1) new technology is required to complete this type of project; (2) the complexity of completing this type of project is high; and (3) it may require a certain expertise to judge the quality of this type of project. Of the 191 projects, the average level of completion uncertainty is 4.515, with two project categories in food and comics presenting the lowest completion uncertainty (*Uncertainty*=3.66) and projects in the technology category presenting the highest completion uncertainty (*Uncertainty*=5.85). Table 1 presents the definitions and descriptive statistics of all variables.

[Insert Table 1 here]

3.3. Results

I first estimated two basic models that exclude geographic and social centrality variables of early backers and then estimated the proposed model with all variables specified in equations (1) and (2). I presented the estimation results of the basic models and the proposed model (using both original and standardized variables) in Table 2. As shown in Table 2, the proposed model significantly improved the goodness of fit as compared to the basic models. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) of the proposed model were significantly lower than those in the basic model. Hence, the main results based on the estimation of the proposed model were used in the following discussion.

[Insert Table 2 here]

Moderating Effect of Uncertainty on Early Backers' Social Impact. As shown in column 2 of Table 2, the main effect of *EBSCC* was significantly positive ($\beta_1 = 64.34$, $p<.05$), but the interaction effect between *EBSCC* and *Uncertainty* on project success was significantly negative ($\beta_3 = -11.69$, $p<.05$). These results suggested that while the impact of early backers in the embedded social network was generally positive, it became weaker as completion uncertainty increased. Thus, H_1 was supported.

Moderating Effect of Uncertainty on Early Backers' Geographic Impact. Surprisingly, I found that the coefficient of *EBGCC* was significantly negative ($\beta_2=-1.272\times10^5$, $p<.01$), while the interactive effect between *EBGCC* and *Uncertainty* on project success was significantly positive ($\beta_4=3.334\times10^4$, $p<.01$). The former result was counterintuitive to us, implying that the impact of the geographic proximity of early backers could be negative. However, as project uncertainty increased, the negative impact of *EBGCC* diminished and might turn positive. Thus, H_2 was supported.[4]

To compare the relative impacts of social proximity with geographic proximity, I estimated the model using standardized variables (i.e., in column 4 of Table 2) and calculated the marginal effects of *EBSCC* and *EBGCC* at the level *k* of project uncertainties by

$\frac{\partial}{\partial EBSCC}\left[\left.\frac{\exp(X_{ip}\vec{\beta})}{1+\exp(X_{ip}\vec{\beta})}\right|\text{uncertainty=k}\right]$ and $\frac{\partial}{\partial EBGCC}\left[\left.\frac{\exp(X_{ip}\vec{\beta})}{1+\exp(X_{ip}\vec{\beta})}\right|\text{uncertainty=k}\right]$, respectively, and

denoted them as $M_{EBSCC,k}$ and $M_{EBGCC,k}$. I presented these results in Table 3, in which I used the theoretical levels of completion uncertainty from 1 to 7 and empirical levels of completion

[4] I further validated the findings with several additional analyses and yielded robust results, which are available upon request.

uncertainty in the data from 3.66 to 5.85. I also plotted Figure 2 to demonstrate how $M_{EBSCC,k}$ and $M_{EBGCC,k\ k}$ varied when using empirical levels of completion uncertainty.

[Insert Table 3 here]

[Insert Figure 2 here]

As shown in Table 3, when project uncertainty was extremely low (e.g., uncertainty=1), the net impact of early backers' social proximity was positive ($M_{EBSCC,1}$=0.5414, p<0.10), but the net impact of early backers' geographic proximity was significantly negative ($M_{EBGCC,1}$=-1093, p<0.01). The former result revealed a herding effect of early backers, which was consistent with existing findings in the social influence literature (e.g., Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992; Zhang and Liu 2012), but the latter was opposite to the neighborhood effect identified in the literature of geographic influence (Bala and Goyal 1998; Bell and Song 2007; Conley and Udry 2010). This finding revealed a deviant effect of early backers, suggesting that early backers who were central in the geographic network could reduce the likelihood of project success when projects had low completion uncertainty. This might be because when the completion uncertainty of a project was low, a major concern to consumer investors lay in the market acceptance of the project. After they observed that early backers were geographically central, they would foresee that the market acceptance of the respective project might be limited in a few locations. As a result, they could become less willing to fund the project, leading to a lower chance of project success. As completion uncertainty increased, however, the net impact of early backers' social proximity became significantly negative ($M_{EBSCC,6}$ = -0.1598, p<0.05), while the net impact of early backers' geographic proximity became significantly positive ($M_{EBGCC,6}$=730.6, p<0.01). These results together also revealed a herding and a deviant effect. The finding of the herding effect implied that geographically central early backers could attract more following investments, which is consistent with the neighborhood effect. On the other hand, the finding of the deviant effect suggested that when a consumer investor observed that a project's early backers were more central in the social network, he might attribute the early backers' investment decision to their excessive financial resources and choose not to follow them, thereby reducing the success chances of respective crowdfunding projects. Empirically, I observed similar patterns as those using theoretical levels of completion uncertainty. For example, for food and comics projects with a low level of completion uncertainty (*Uncertainty*=3.66), I found that the net impact of social proximity of early backers was positive ($M_{EBSCC,3.66}$=0.1212, p<0.1), while the net impact of geographic proximity of early backers was negative ($M_{EBGCC,3.66}$=-537, p<0.01). For technology projects with a high level of completion uncertainty (*Uncertainty*=5.85), the net impact of social proximity of early backers was negative ($M_{EBSCC,5.85}$=-0.141, p<0.05), but the net impact of geographic proximity of early backers was positive ($M_{EBGCC,5.85}$=656.3, p<0.01).

4. Discussion and Conclusion

4.1. Theoretical Contribution

While crowdfunding presents a novel method for entrepreneurs and small businesses to seek financial support from consumers, it also involves enormous uncertainty for both project creators and consumer investors through an interactive process (Bender *et al.* 2019; Moysidou and Hausberg 2020). This process is characterized by the interactive information exchange between early backers and peers and between project creators and backers, enabled by the innovations of interactive technologies and platform ecosystems (Wang 2021).

Thus, in addition to refining the project information broadcasted to consumers, it is important for entrepreneurs to understand how consumer investors learn from and influence each other in their funding decisions (Colombo *et al.* 2015). This study addresses this issue by explicitly examining how early consumer investors influence others in their social and geographic networks on a crowdfunding platform and how such influences vary with the completion uncertainty of crowdfunding projects and differ in their social and geographic networks. By identifying the project completion uncertainty as a moderator of the herding effect (e.g., Bikhchandani *et al*. 1992; Zhang and Liu 2012) and neighborhood effect (e.g., Choi *et al*. 2010; Lee and Bell 2013) in crowdfunding, the theoretical development and empirical findings make critical contributions to the literature of social influence and crowdfunding and provide essential implications to innovators and crowdfunding platforms.

4.2. Managerial Implications

The empirical findings provide managerial implications to both innovators (i.e., project creators) and crowdfunding platforms. For project creators, the findings provide guidance to identify the right crowd and enhance the chance of success of their projects. Specifically, project creators should consider two critical factors when targeting and attracting backers: (1) the completion uncertainty of their projects and (2) backers' social and geographic relationship with other crowdfunders on the crowdfunding platform. If a project involves low completion uncertainty, then how to signal a broad market acceptance of this project could be the key to success. To do so, project creators should target those who are socially close to other crowdfunders. In contrast, if a project entails high completion uncertainty, the findings suggest that the project creator should target those who are geographically close to other crowdfunders. For example, the data reveal that a large number of crowdfunders on Kickstarter locate in San Francisco and New York City. For projects using advanced technology or requiring a complex manufacturing process, the project creators could focus on crowdfunders in these two cities so that other crowdfunders in the same cities may follow suit, thereby enhancing the success of their projects.

4.3. Limitations and Future Research

This study has several limitations that provide opportunities for future research. First, the empirical investigation is based on consumer investors' funding behaviors on Kickstarter, a reward-based crowdfunding platform. It would be interesting for future research to explore if the findings still hold when data from different formats of crowdfunding are available. Second, the current study lacks explicit evidence regarding the underlying forces leading to such impacts. Future research can further examine the underlying mechanism for the different impacts of early backers if field experiments are possible. Overall, crowdfunding raises many interesting issues for future research. For example, by applying advanced machine learning technologies, such as computer vision, future research can explore the influence of user-generated content, such as videos and pictures, on consumers' investment decisions (e.g., Ma and Palacios 2021). Moreover, given the potential of using misinformation or disinformation to stimulate the herding effect, it would be interesting to explore the policy implications of investors' peer influences on small business financing (Berger and Udell 1998).

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Table 1: Variable Definitions and Descriptive Statistics

Variable	Definition	Mean	Standard Deviation
Success	Success =1 if the project achieved its funding goal; 0 otherwise.	0.466	0.500
Early backer's social closeness centrality (*EBSCC*)	Measured in closeness centrality, i.e., $EBSCC_i = \frac{N-1}{\sum_{j=1, j\neq i}^{N-1} d_s(b_i, b_j)}$, where $d_s(b_i, b_j)$ denotes the shortest social distance between vertices b_i and b_j.	0.518	7.158×10^{-2}
Early backers' geographic closeness centrality (*EBGCC*)	Measured in closeness centrality, i.e., $EBGCC = \frac{N-1}{\sum_{j=1, j\neq i} d_g(b_i, b_j)}$, where $d_g(b_i, b_j)$ denotes the shortest geographic distance between early backer b_i and other crowdfunders b_j.	1.936×10^{-4}	3.923×10^{-5}
Project's geographic closeness centrality to backers (i.e., *PBGCC*)	Measured in closeness centrality, i.e., $PBGCC_p = \frac{N}{\sum_{i=1}^{N} d_g(p, b_i)}$, where $d_g(p, b_i)$ denotes the shortest geographic distance between the project *p* and the backer b_i in kilometers.	2.070×10^{-4}	2.421×10^{-5}
Completion uncertainty of crowdfunding projects	The perceived uncertainty of completion in the project category, measured on a 3-item scale.	4.515	0.533
Distance	The geographic distance between the project creator and early backers.	4.427×10^{3}	3.805×10^{3}
Goal	The amount of funds that a project aims to raise in US dollars.	2.076×10^{4}	5.084×10^{4}
Funding period	The length of the time period in which the project raises funds, measured in days.	32.283	10.233
Funds pledged in week 1 (PLGDW1)	The total amount of funding in US dollars that backers pledged in the first week of the funding period.	3.598×10^{3}	1.100×10^{4}
Average funds pledged in week 1 (AVGPLGDW1)	The average amount of funding in US dollars that backers pledged in the first week of the funding period.	53.582	55.013
Failed	Total number of projects by a project creator that failed before the focal project.	0.325	0.781
Succeeded	Total number of projects by a project creator that succeeded before the focal project.	0.147	0.615
Backed	Total number of projects backed by a project creator before the focal project.	9.540	78.689
Facebook Friend	The number of Facebook friends that a project creator had before the focal project.	416.67	663.87

Table 2: Impact of Geographic and Social Proximity on Project Success

Variables	Basic Models		Proposed Model	
	Basic Model 1	Basic Model 2	Using Original Variables	Using Standardized Variables
EBSCC		2.031 (11.18)	64.34^{**} (30.94)	-0.1047 (0.1728)
EBGCC		1.034×10^{4} (2.719×10^{4})	$-1.272\times10^{5***}$ (4.620×10^{4})	0.0799 (0.1408)
EBSCC × Uncertainty			-11.69^{**} (5.556)	-0.2703^{**} (0.1285)
EBGCC × Uncertainty			$3.334\times10^{4***}$ (7813)	0.4225^{***} (0.0990)
EBSCC × EBGCC		-1.902×10^{4} (5.187×10^{4})	-5.455×10^{4} (5.609×10^{4})	-0.1532 (0.1575)
Distance		-5.564×10^{-5} (4.280×10^{-5})	$-1.000\times10^{-4**}$ (4.500×10^{-5})	-0.3946^{**} (0.1725)
PBGCC		$1.525\times10^{4***}$ (4713)	$1.444\times10^{4***}$ (4661)	0.3320^{***} (0.1039)
Uncertainty	0.8590^{***} (.2686)	0.6332^{*} (.3601)	-0.5966 (3.286)	-0.0656 (0.1333)
Goal	$-5.000\times10^{-5***}$ (3.200×10^{-5})	$-5.735\times10^{-4***}$ (4.863×10^{-5})	$-6.300\times10^{-4***}$ (5.700×10^{-5})	-26.32^{***} (2.379)
Funding Period	0.0584^{***} (0.0164)	0.1457^{***} (0.0277)	0.1492^{***} (0.0292)	0.9051^{***} (0.1770)
PLGDW1	$9.840\times10^{-4***}$ (7.200×10^{-5})	$1.105\times10^{-3***}$ (1.070×10^{-4})	$1.220\times10^{-3***}$ (1.270×10^{-4})	54.31^{***} (5.658)
AVGPLGDW1	0.0441^{***} (0.0036)	0.0528^{***} (.00546)	0.0562^{***} (.00562)	2.330^{***} (0.2328)
Failed	-0.4558^{*} (0.2763)	-0.6050 (0.3686)	-0.7518^{*} (0.4067)	-0.4456^{*} (0.2410)
Succeeded	0.3091 (0.3884)	0.6254 (0.4557)	0.8488 (0.5926)	1.321 (0.9224)
Backed	0.0331^{***} (1.970×10^{-3})	0.0378^{***} (3.005×10^{-3})	0.0407^{***} (3.450×10^{-3})	6.249^{***} (0.5290)
Facebook Friends	-6.000×10^{-5} (1.690×10^{-4})	-4.009×10^{-5} (2.647×10^{-4})	1.980×10^{-4} (2.690×10^{-4})	0.1002 (0.1360)
Intercept	-3.134^{***} (1.165)	-8.780 (6.047)	-6.636 (17.52)	33.42^{***} (3.654)
Log-Likelihood Value	-347.625	-207.022	-194.761	-194.761
AIC	715.249	444.044	423.522	423.522
BIC	783.766	542.679	535.308	535.308
Sample Size	5301	5301	5301	5301

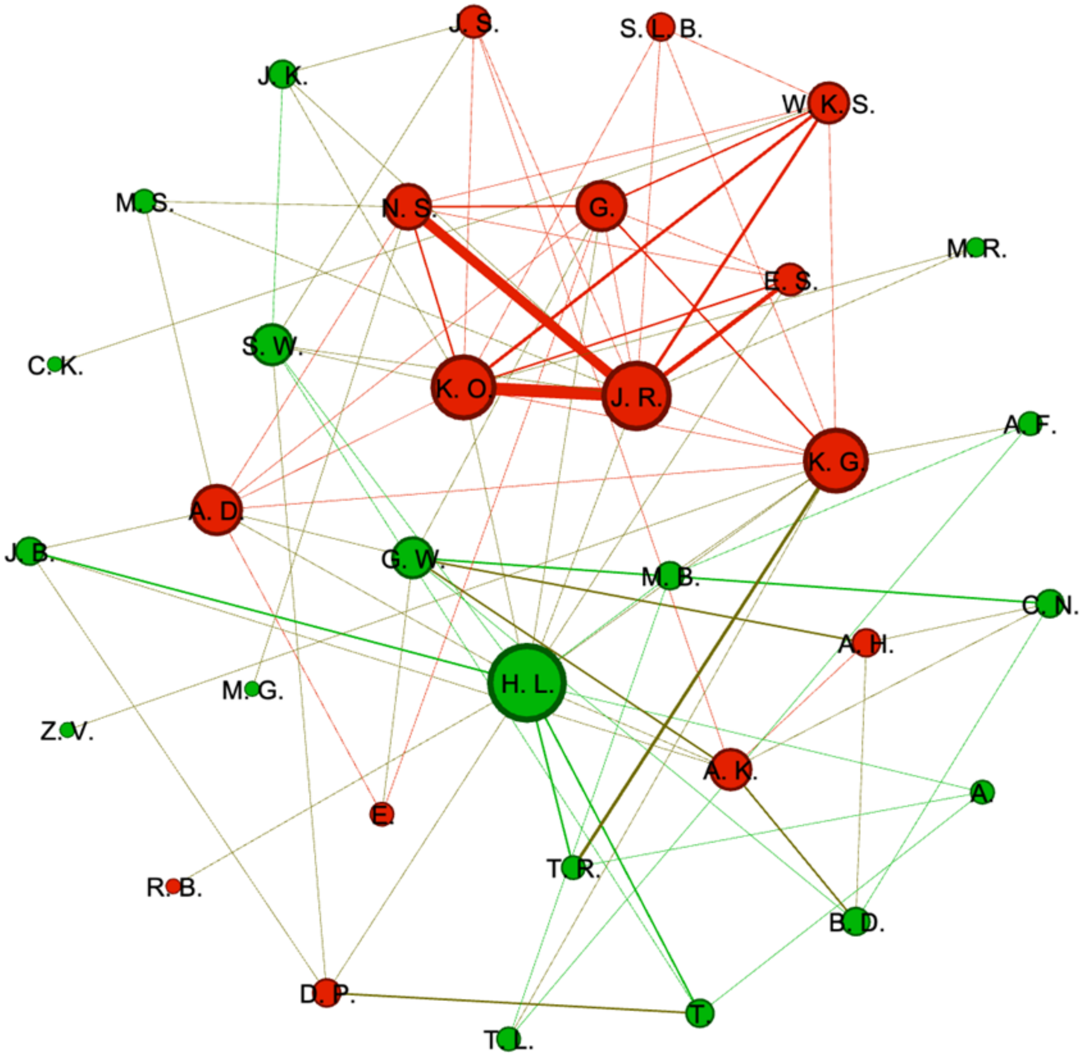
Note: ***: p<0.01; **: p<0.05; *: p<0.1.
Basic model 1: without incorporating early backers' network positions.
Basic model 2: Without incorporating the interactions between early backers' network positions and uncertainty.

Table 3. Marginal Effect of Early Backers' Social and Geographic Closeness Centrality

Project Uncertainty		**Marginal Effect of Social Closeness Centrality**		**Marginal Effect of Geographic Closeness Centrality**	
		Using Original Variables	Using Standardized Variables	Using Original Variables	Using Standardized Variables
Theoretical Levels of Project Uncertainty	1	0.5414*	0.0388*	-1093***	-11.53***
	2	0.3898*	0.0279*	-1023***	-8.437***
	3	0.2356*	0.0169*	-807.8***	-5.341***
	4	0.0715‡	0.0051‡	-285.6**	-2.245***
	5	-0.0576*	-0.0041*	138.8**	0.8510***
	6	-0.1598**	-0.0114**	730.6***	3.947***
	7	-0.3504**	-0.0251**	981.7***	7.043***
Empirical Levels of Project Uncertainty	3.66	0.1212*	0.0087*	-537.0**	-0.0150***
	3.71	0.1135*	0.0081*	-496.9**	-0.0142***
	3.88	0.0883‡	0.0063‡	-364.0**	-0.0114***
	4.03	0.0674‡	0.0048‡	-267.5**	-0.0091***
	4.19	0.0458	0.0033	-177.0**	-0.0067***
	4.36	0.0231	0.0017	-99.42*	-0.0041*
	4.37	0.0218	0.0016	-95.47*	-0.0039*
	4.56	-0.0035	-0.0002	-23.49	-0.0010
	4.79	-0.0330	-0.0024	59.18‡	0.0024‡
	4.90	-0.0462‡	-0.0033‡	98.09**	0.0040**
	4.96	-0.0531*	-0.0038*	121.7**	0.0048***
	5.85	-0.1410**	-0.0101**	656.3***	0.0150***

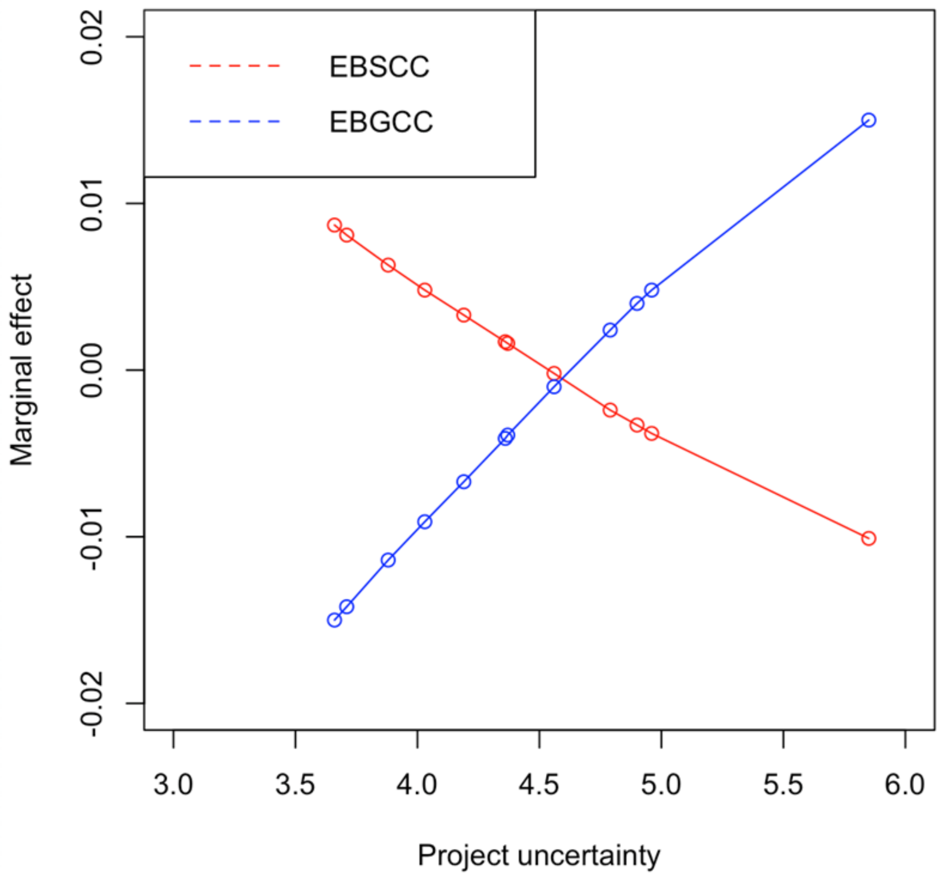
Note: ***: p<0.01; **: p<0.05; *: p<0.1; ‡: p<0.1 (one-tailed).

Figure 1. A Subnetwork of 33 Crowdfunders Extracted from the Data



Note: Red nodes represent early backers and green nodes represent followers. The thickness of the line between two nodes indicates the strength of connection, which is determined by the number of shared projects between two backers.

Figure 2. Marginal Effects of Early Backers' Social and Geographic Closeness Centrality



Note: EBSCC and EBGCC: the social closeness centrality and geographic closeness centrality of early backers, respectively. Marginal effects are derived based on standardized variables and empirical levels of project uncertainty (see Table 3).