Collective Dynamics of Crowdfunding Networks

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Abstract

The crowdfunding phenomenon has garnered a considerable amount of attention in recent years. Several online crowdfunding platforms have risen to prominence; they can be characterized as two-sided marketplaces. Recent research reveals initial insights into the dynamics and characteristics of crowdfunding networks arising from such marketplaces. This research, though, is restricted primarily to analyses of static network snapshots and at the dyadic level. In this study, we use a large longitudinal dataset to analyze the behavior of actors on both sides of the market who promote their own and fund others’ projects. We investigate the influence of endogenous and exogenous effects on the dynamics of crowdfunding networks. Our results provide evidence for mechanisms promoting a hierarchical network organization and the absence of homophily-related mechanisms regarding gender or geographic distance. Moreover, we establish that experienced and popular project creators fund fewer projects.

1. Introduction

In recent years, crowdfunding has garnered considerable attention. Belleflamme et al. define crowdfunding as “an open call, mostly through the Internet, for the provision of financial resources either in form of donation or in exchange for the future product or some form of reward and/or voting rights” [12]. Crowdfunding initially appeared in 2006 [35] and has its roots in crowdsourcing [27]. In crowdsourcing, the “crowd” works together collaboratively on a common goal; in crowdfunding, the crowd collectively provides financial resources for products and services to be developed. Thus, crowdfunding is its own unique category of fundraising [41].

Passage of the Jumpstart Our Business Startups Act (JOBS Act) [4], a law intended to encourage funding of U.S.-based small businesses by easing various securities regulations, was the first attempt to regulate crowdfunding, and crowdfunding platforms now seem poised to become even more prominent. One platform, Kickstarter [2], has since its 2009 launch provided over $1 billion from more than 6 million people to 60,000-plus projects [3] – making it the world’s largest funding platform for creative projects.

Crowdfunding and Kickstarter in particular has caught the attention not only of consumers and startups but also researchers. Recent research on crowdfunding has focused on dynamics [41], geography [5], and economic [6] characteristics of crowdfunding markets. Scholars have also analyzed the motivators and deterrents for participation [22], and examined social influence in crowdfunding markets [15]. These studies investigate the coherence between these aspects and funding success. These studies distinguish between two types of users: supporters and project creators. However, crowdfunding platforms allow users to play both sides of the market, that is, to create and support projects. Hence, crowdfunding markets can be characterized as two-sided markets [21] in which users can act both as entrepreneurs and investors. There are, though, obvious differences between users who participate as investors in crowdfunding markets and traditional investors in an entrepreneurial context (e.g., venture capitalists or business angels). Participants in crowdfunding markets invest less capital and they have a lower financial risk should an investment go wrong. Traditional investors are experienced individuals or organizations with considerable capital and knowledge in evaluating potential investment opportunities [6, 7], and bring additional value to startups, such as industry knowledge and relationships [28]. Moreover, there is strong evidence that participants in crowdfunding markets assess the value and risk of investments in novel products, services and organizations differently than traditional investors. For example, the smart watch Pebble was rejected by venture capitalists before it was funded through a highly successful Kickstarter campaign [41]. Earlier research on the funding behavior of project creators was limited to the dyadic level of analysis and primarily based on static representations of the network comprised of their funding relationships. Zvilichovsky et al. [58] are the first to analyze crowdfunding from a two-sided market perspective. They show that project creators, who act also as supporters, create a sub-community of
supporters that exhibits reciprocal behavior in supporting other projects [58].

We address the aforementioned restrictions by analyzing the behavioral mechanisms of project creators who also act as supporters on Kickstarter. We collected longitudinal social network data from Kickstarter and apply stochastic actor-based modeling (ABM) [48] to that data, which allows us to explore behavioral mechanisms. Our research question is: “What mechanisms govern the dynamics of crowdfunding networks in which project creators play both sides of the market?”

In the next section, we provide background information on potential behavioral mechanisms in the described scenario and develop our hypotheses accordingly. Then, we describe the data and methods. Subsequently, we present the results and conclude by discussing the implications and limitations of our study.

2. Background

In this section, we provide background information on the mechanisms and features of crowdfunding platforms. Further, we motivate and develop our hypotheses regarding behavioral mechanisms in crowdfunding markets, which affect the structural properties of the networks formed by project creators and their support relationships.

2.1. Crowdfunding Platforms

Crowdfunding platforms typically provide three central mechanisms to enable project creators and potential funders to fund a project collectively. First, they allow creators to display publicly project-related information, including text, pictures, and videos. Second, they make projects accessible and visible to the public, usually by providing project overviews and search interfaces. Third, they allow users to participate in funding a project. Beyond these basic mechanisms, platforms also provide the features typical of social media platforms: display of user profiles, communication, search, and privacy-related features (see [32]). In this paper, we are interested in funding relationships, which can be represented as directed ties between two project creators (or actors) A and B. A’s decision to support B is based on information available to A. Since many crowdfunding platforms provide a comprehensive amount of social and digital media, A typically has access to rich information on the project, its creator, and its supporters. While others have already investigated the impact of project-related information on successful funding [22, 41, 58], we focus on the effect of information on creators and supporters.

2.2. Reciprocity

The theory of social exchange [13] suggests two forms of exchange based on two different principles of reciprocity [54]. Indirect reciprocity, or generalized exchange, means one individual A gives to B but receives back from a third actor, C [54]. Mutual reciprocity, or direct exchange, operates between two individuals A and B: A gives to B and receives back from B. There is a strong evidence for mutual reciprocity in the organizational context. For example, venture capitalists tend to build relationships by sharing high-quality deals with established exchange partners [51]. Recent studies in a crowdfunding networks context provide evidence for mutual reciprocity [40, 58]. Zvilichovsky et al. [58] find evidence for mutual reciprocity by analyzing supporting activities of projects creators. They conclude that supporting the projects of other project creators is a rewarding strategy for successful funding. Moreover, project creators are much more active in supporting projects than are regular users [58]. Thus, mutual reciprocity seems to be an important effect; we include it in our model. Following this argument, we hypothesize:

H1. There is a greater likelihood that project creator A supports project creator B if B also supports A.

2.3. Transitivity & Hierarchy

Transitivity (or transitive closure) is a property of three interconnected individuals A, B, and C. The connection from B to C is referred to as a transitive tie if A has a directed connection to B and C. This triadic pattern is called a transitive triplet (see Figure 1a). Similarly, a triad forms a three-cycle if all involved individuals are connected by directed relationships that flow in one direction from one actor to the next (see Figure 1b).

Figure 1. Transitive triplets and three-cycles

While similar, both patterns have different implications for the structure of a network and represent different behavioral preferences. If actors
have a positive tendency to form transitive triplets, they promote a hierarchical ordering. The opposite is true for three-cycles [48]. Several theories and effects, such as network closure [19] and balance [26], suggest a positive tendency towards the formation of transitive triplets in organizational and social settings (see [20]). There is strong empirical support for this effect and it has often been established that organizations tend to form transitive relationships with their partners’ partners [9, 24]. The tendency to form three-cycles, however, is a less-common property of such systems [48]. The frequent occurrence of three-cycles can be interpreted as a preference for generalized (indirect) exchange [48]. This effect is also referred to as generalized reciprocity. In contrast to reciprocity (restricted exchange), generalized exchange assumes an indirect reciprocation of exchanged values, that is, A supports B and B returns the favor to an unrelated actor C [10]. On a crowdfunding platform such as Kickstarter, it is safe to assume that project creators A and B share a common interest if A supports B or vice versa. Accordingly, both are likely to be interested in similar projects. Thus, their mutual likelihood to support such projects is higher than for an unrelated pair of creators. Moreover, if A supports B, B is more likely to be aware of A and the projects supported by A. If both share a common interest, as assumed above, this further increases the likelihood of a transitive closure between A, B, and a third project creator. Consequently, we expect a positive tendency towards the creation of transitive triplets. For the same reason, project creators should be less likely to form three-cycles. Thus, the likelihood of three-cycles and generalized exchange is further reduced. In summary, we propose the following hypotheses:

\[ H2a. \text{ The likelihood that a project creator supports another creator by closing a transitive triplet is higher than the likelihood of supporting a random creator.} \]

\[ H2b. \text{ The likelihood that a project creator supports another creator by closing a three-cycle is higher than the likelihood of supporting a random creator.} \]

2.4. Homophily, Gender, and Geography

Homophily is the tendency of people with similar sociodemographic or behavioral characteristics to interact more with similar people rather than with others [37]. One can examine homophily, for example, in gender or geography [36]. Gender homophily means individuals are more likely to choose partners of the same gender for interaction. Male VCs show homophilous behavior based on gender because of shared networks and social preferences [44, 52]. Harrison and Mason [25] suggest that female business angels are slightly more likely to invest in women-owned businesses. Women’s participation in the entrepreneurial context is rather low both in the venture capital industry [14] and in founding startups [33]; in both, they are a minority. Where women are in the minority, they find it more difficult to form relationships [30]. Therefore, there may be a lower number of interesting projects for females, which may affect their participation in crowdfunding markets. Gender can influence risk-taking propensity. Women exhibit relatively more risk aversion in making financial decisions [31], especially in an entrepreneurial context [45]. However, the percentage of received investments (25%) by women is above the market yield rate [50], which indicates that when women do seek venture capital they receive more than male entrepreneurs. Considering these findings, we argue that homophily, gender effects, and risk-taking propensity have specific consequences for project creators’ behavior in a crowdfunding context:

\[ H3a. \text{ Female project creators are less likely to support project creators than male project creators.} \]

\[ H3b. \text{ Female project creators are more likely to receive support than male project creators.} \]

\[ H3c. \text{ Female project creators are more likely to support female project creators, and male project creators are more likely to support male project creators.} \]

\[ H3d. \text{ Project creator A is more likely to support project creator B if B also supports A, and if both are of the same gender.} \]

Geographic homophily is the tendency of people closer in geographic location to interact more with each other than with those who are distant [37]. VCs tend to locate their headquarters in areas with a lot of startups [17, 53]. Sorenson and Stuart [51] find that VCs invest twice as much in companies within a 10-mile radius of their headquarter than in those more than 100 miles away. Thus, they are homophilous with the respect to geography. There are also studies that explore the geographical effects in crowdfunding [5, 6, 41]. Agrawal et al. [5] analyzed the influence of distances between supporters and project creators in the United States on funding success. The average distance between creators and funders was approximately 3,000 miles and is less important in the crowdfunding setting than in a traditional funding setting [5]. However, another study that explored the influence of geography in crowdfunding shows that crowdfunding projects are not evenly distributed across the United States; rather, they tend to be in metropolitan areas with a high concentration of talented and creative people [41]. The talent of an
area’s population may affect the number of project creations in one geographic area as well as funding success [41]. Thus, if there were a positive tendency towards geographic homophily, we would expect project creators to prefer supporting others within a small radius (e.g., 10 to 100 miles). Mollick [41] states that geography plays an important role in the success of crowdfunding efforts, but it is not clear whether and to what extent geography influences project creators. Thus, we propose,

**H4a. Project creator A is more likely to support project creator B if their geographic separation is relatively small.**

**H4b. Project creator B is more likely to support project creator A if B supports A and their geographic separation is relatively small.**

### 2.5. Experience

Entrepreneurs with firm-founding experience are expected to have more skills and social connections than inexperienced entrepreneurs [56]. Such skills and the resulting social capital could give experienced founders some advantage in the process of raising venture capital [56]. Founding experience increases the likelihood of being funded directly by a VC [29]. VCs have come to believe that the experience of those who have already been founders is the best indicator of future performance, and consequently are more likely to fund these projects [11, 16]. Helping fund a project on Kickstarter provides supporters several project privileges. They get access to project status announcements, can monitor project progress, and are even notified automatically about a supported project’s status. Thus, they gain access to information unavailable to non-supporters. Novice project creators may use this information to gain experience from other projects or learn from other project creators. In the case of experienced project creators who may no longer need to learn from other project creators because they already have experience with more than one project creation, their support for other projects may diminish. If the above is true, we propose the following hypotheses:

**H5a. Experienced project creators are more likely to be supported by other project creators than are inexperienced project creators.**

**H5b. Experienced project creators are less likely to support other project creators than are inexperienced project creators.**

### 2.6. Popularity

An actor’s popularity can be defined as the number of the actor’s incoming ties [55]. For example, startup founders gain popularity by performing networking activities [8, 56]. As a result, they generally have greater access to and control of relevant resources (e.g., social capital, information, etc.). In crowdfunding, high popularity means project creators receive more support. Higher popularity may increase a project’s visibility on Kickstarter and hence the creator’s visibility as well. Visibility can be magnified by the Matthew Effect [38, 39]; credit will typically be given to project creators already supported by a high number of supporters. High-supported projects have a higher visibility on a crowdfunding platform and hence attract supporters who may promote the project to other potential supporters or external media, thus increasing the project’s attraction. Extremely popular projects are also featured in Kickstarter’s “popular projects” category, which increases visibility considerably [41]. Supporters on crowdfunding platforms invest in products or services rather than in organizations, and act more like consumers. To minimize risk, they may use publicly available information about the actual success status of a creator’s project. Potential supporters can also see whether a supporter is a project creator by reviewing his “projects created” history. The higher the amount of capital raised by the project creator, the lower the risk for the supporter. Generally known as the “penguin effect,” this describes a kind of herding behavior in regard to risk taking [18]. Earlier studies found evidence of herding behavior in an organizational context [57] and even on Kickstarter [34]. However, Kuppuswamy and Bayus state that “[a]ditional studies are needed to more completely understand the possible herding behavior of users in crowdfunding communities” [34]. Project creators who are very popular on a crowdfunding platform and receive a high level of support may be very thankful and hence want to reciprocate by supporting another project creator. A high number of reciprocal ties would reveal this behavior. Therefore, we propose

**H6a. The higher the popularity of project creator A, the higher the likelihood that A receives even more support from other project creators.**

**H6b. The higher the popularity of project creator A, the higher the likelihood that A supports other project creators.**

### 3. Methods

In this section, we describe our data collection and sampling approach as well as the methodology used to test our hypotheses.
3.1. Data Collection and Sample

This study is based on data collected from Kickstarter, which is currently the leading crowdfunding platform on the Web. We used a self-written Web crawler to collect the properties of all projects, their creators, and their supporters between April 2009 and April 2014. The crawler was programmed to access Kickstarter’s search interface, which provides a complete list of finished and ongoing projects. For each project, we collected the status (i.e., failed, successful, cancelled, suspended, or live), funding goal, launch date, deadline, creator, and list of project creators supporting the project. In addition, we collected the nickname, first name, origin, and date of platform entry for each creator in our list. The resulting dataset contains 128,841 projects launched by 111,617 project creators. Further, we restricted the overall dataset to the Kickstarter creator network. First, we removed all ongoing, cancelled, and suspended projects as well as deleted user accounts. We also removed any project with an extremely low (<$100) or extremely high (> $1,000,000) funding goal. Such projects, which often have very specific attributes that tend to overshadow other dynamic forces, tend to create a skew when evaluating population results [41]. Next, we removed observations involving non-U.S.-based project creators. These restrictions reduced the dataset to 71,380 valid projects and 61,964 creators. To study the mechanisms governing the creator network in a stable state of the platform, we considered projects of users that joined the platform in 2012. Of those, we considered only the 200 most active users. We removed users from our sample who had not supported at least one other project. Next, we used the resulting group of active creators to draw a snowball sample [23] that included all creators that had supported or had been supported by one of the actors in the group. Our final sample contains 2,241 projects, 1,477 active creators, and 6,394 support relationships between those. We collected additional creator attributes to test our gender- and geography-related hypotheses. Based on a review of user and project profiles, we manually coded the gender of each creator, having identified male and female creators according to their real names, profile pictures, project videos, project descriptions, and – if available – external websites and Facebook profiles. We translated the creators’ locations into geolocations using the Google Maps Geocoding API [1], which we then used to compute their pairwise geographic distances. We divided our sample into five successive six-month periods to identify patterns of change in the network structure resulting from the support relationships between project creators. This allowed us to examine network dynamics and the process of network evolution. Five such periods is a sufficient number to estimate a reliable actor-based model (see [48]). Furthermore, with a period length of six months, we can safely assume that each period contains a sufficient number of changes to increase the stability of estimated parameters. Moreover, we checked the distribution of user activity during the observation period and found a period length of six month to produce the most stable waves.

3.2. Analysis

To test the proposed hypotheses, we use stochastic actor-based models (ABMs), which have been introduced by Snijders [46, 47, 49] and discussed in detail by Ripley et al. [43] and Snijders [48]. ABMs have been developed to analyze network changes over time, with the goal of understanding the mechanisms that govern network evolution. A fundamental assumption of such models is that network change is caused by the individual actions of actors, who maintain, establish and dissolve ties. The behavior of actors, in turn, is affected by exogenous and endogenous effects. Endogenous effects refer to the tendency of actors to establish or dissolve ties based on the network structure in which they are embedded. Thus, endogenous effects describe structural phenomena, such as an actor’s tendency to form reciprocal ties or to close transitive triplets.

Exogenous effects are based on actor attributes such as age and gender [48]. They describe, for example, an actor’s preference to establish (or dissolve) ties with other actors of the same gender, age, or origin. It is worth mentioning that, in ABMs, exogenous variables are not used to predict endogenous variables, as is the case in causal modeling. Rather, both types of effects describe the behavioral tendencies of actors, and, in turn, explain structural tendencies of the network.

To estimate a statistical model that explains network dynamics based on a set of modeled effects, ABMs combine the use of empirically collected longitudinal network data, which is split into multiple consecutive time intervals (waves), and computer simulation. For each wave of network data, all existing ties of the network are aggregated to a snapshot, which represents the network structure at the end of the wave. The network changes from one wave to another are then simulated as a sequence of so-called mini-steps. In each mini-step, a single actor is chosen to make a choice: he can do nothing, create a tie, or dissolve a tie.

At the core of this process, repeated computer simulations are used to determine how the actor’s decision is biased towards the specified set of endogenous and exogenous effects. The simulation
algorithm uses the empirically observed network structure and the individual actor’s attributes to capture an actor’s preferences in an evaluation function. This function describes the probability of his actions and is a linear combination of the specified effects. The statistical parameters of the function represent the estimated impact of an effect on an actor’s decision. If a parameter is 0, there is no evidence of an influence of the corresponding effect. Positive parameters indicate a positive influence of the effect on a decision; negative parameters suggest a negative influence. Parameter estimates are computed using all waves. Thus, if the algorithm is able to reconstruct the transition from each wave to the next reliably using the computed estimates (as indicated by the convergence statistics reported in Sec. 4), they can be considered to be stable across all waves. Since this is the case for all specified effects of the hypotheses, Snijders [48] and Ripley [43] provide a comprehensive overview on available effects and their interpretation. The decision about the inclusion of modeled effects is guided by theory. We developed 13 hypotheses based on theoretical considerations regarding the behavior of creators of crowdfunding projects, which receive and provide support from and to fellow creators. In the following, we refer to project creators simply as actors and to their support relationships as ties. To test the proposed hypotheses, we now specify the effects we include in our model. These effects are the direct translations of the hypothesized behavior of project creators into a network representation. We specify our ABM as follows.

At the nodal level, we include two endogenous popularity effects. The in-degree popularity effect measures the tendency of actors with many ingoing ties (i.e., popular actors with many supporters) to receive even more incoming ties (H6a), whereas the out-degree popularity effect measures whether a popular actor has a higher likelihood of producing outgoing ties than less-popular actors (H6b). The only endogenous effect considered on the dyadic level is the reciprocity effect, which estimates an actor’s tendency to create reciprocal ties (H1). We also include two endogenous triadic effects, namely transitive triplets and three-cycles, which refer to the phenomenon of transitive closure (H2a, H2b).

The exogenous effects included in our model allow us to control for the covariates gender and experience as well as geographic distance. The experience covariate is a dynamic covariate and measures the number of projects an actor has created up to each of the five periods under consideration. For gender and experience, we include alter as well as ego effects (H3a, H3b, H5a, H5b). Alter effects refer to the influence of a covariate on an actor’s likelihood of receiving ingoing ties. Ego effects do the same for the likelihood of creating outgoing ties. Considering gender and geographic distance, we include two dyadic covariates. The dyadic gender effect controls for the preference of actors to create ties with alters of the same gender (i.e., gender homophily – H3c), while the geographic distance effect accounts for the actors’ tendency to support nearby or distant actors (H4a).

Finally, we also include the individual interaction of gender homophily and geographic distance with reciprocity (H3d, H4b).

Following a forward selection approach, we estimated 13 models in total. Beginning with endogenous effects, we included exogenous and interaction effects in a stepwise procedure and then validated our results by performing a backward selection procedure.

In the next section, we report descriptive statistics, the results of our analysis, and model fit as suggested by Snijders [48]. Since our results were stable across all estimated models, we report only two models – a reduced version that includes only endogenous effects and a full version with both endogenous and exogenous effects. We used RSiena (version 1-232) to compute all actor-based models.

4. Results

Of the 1,477 project creators in our sample, we identified 24.17 percent as female and 75.83 percent as male. The mean (median) of projects created per user at the end of our observation period is 1.54 (1.0). Project creators are separated by an average distance of 1,235 miles; the median is 1,215 miles.

### Table 1. Tie changes

<table>
<thead>
<tr>
<th>Tie change</th>
<th>Distance</th>
<th>Jaccard coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 → 0</td>
<td>0 → 1</td>
<td>1 → 0</td>
</tr>
<tr>
<td>From t1 to t2</td>
<td>2,175,088</td>
<td>2,468 0</td>
</tr>
<tr>
<td>From t2 to t3</td>
<td>2,174,771</td>
<td>317 0</td>
</tr>
<tr>
<td>From t3 to t4</td>
<td>2,174,517</td>
<td>254 0</td>
</tr>
<tr>
<td>From t4 to t5</td>
<td>2,174,414</td>
<td>103 0</td>
</tr>
</tbody>
</table>

### Table 2. Densities and average degrees

<table>
<thead>
<tr>
<th>Observation time</th>
<th>Density</th>
<th>Average degree</th>
<th>No. of ties</th>
<th>l1</th>
<th>l2</th>
<th>l3</th>
<th>l4</th>
<th>l5</th>
<th>l6</th>
</tr>
</thead>
<tbody>
<tr>
<td>t1</td>
<td>0.001</td>
<td>1.690</td>
<td>2,496</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t2</td>
<td>0.002</td>
<td>3.361</td>
<td>4,964</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t3</td>
<td>0.002</td>
<td>3.575</td>
<td>5,281</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t4</td>
<td>0.003</td>
<td>3.747</td>
<td>5,535</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>t5</td>
<td>0.003</td>
<td>3.817</td>
<td>5,638</td>
<td></td>
<td></td>
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</table>
Table 1 reports the amount of changes observed between each pair of consecutive periods. For example, between period 1 and 2, we establish a difference of 2,468 new support relationships (0 → 1), while 2,496 ties already existed in the first period (1 → 1). Note that once the funding period of a Kickstarter project has been completed, it is no longer possible to revoke one’s support for this project. Thus, support relationships cannot dissolve (1 → 0). Further, we report the Jaccard coefficient, which represents the amount of change between two periods [48]. Values close to 1 indicate little network change, while values close to 0 describe very unstable networks. According to Snijders et al. [48], values above 0.3 are recommended to estimate reliable ABMs. In our case, all coefficients are well above the suggested threshold. It is worth noting that a large fraction of the observed changes occur between periods 1 and 2. Thus, the average degree increases rapidly between the first two periods and stabilizes during the subsequent periods (Table 2). This indicates that most of the users in our sample created their projects shortly after joining the platform.

Both actor-based models reported in Table 3 show excellent convergence statistics, that is, the t-ratios reported by RSienna were all well below an absolute value of 0.1 for each parameter. As described by Snijders et al. [48], parameter estimates for included effects are assumed to follow a normal distribution. Thus, they can be tested for significance using a standard t-test (Table 3).

The first model is restricted to endogenous effects. We find that these all have a significant influence on the formation of ties in the network. To be more specific, we observe a positive tendency to establish reciprocal ties and transitive triplets. Moreover, project creators have a negative tendency towards the creation of three-cycles. Further, popular project creators have a slightly higher likelihood of receiving additional support from other creators. At the same time, the negative estimate for the out-degree popularity effect suggests that popular creators have a lower likelihood of supporting others. The second model includes all endogenous effects as well as exogenous and interaction effects. Estimates for endogenous effects are comparable to those of the first model. We find a highly significant effect of gender on the likelihood of receiving support and supporting others. A positive estimate for the gender-alter effect suggests a higher likelihood of females receiving support. The negative estimate reported for the gender-ego effect indicates that females have a lower likelihood of supporting others. In addition, we observe a negative experience-ego effect, indicating that project creators with a high number of prior projects have a lower likelihood of supporting others. Surprisingly, there is no evidence of geographic distance on project support in general and only a very small effect of distance on reciprocity; project creators relatively nearer to each other seem to have a slightly higher likelihood of reciprocal support.

In summary, we find strong support for $H_1$, $H_2a$, $H_2b$, $H_3a$, $H_3b$, $H_5b$, $H_6a$, $H_6b$, and weak support for $H_4b$. Since gender homophily, the experience-alter effect, and the basic dyadic effect of geographic distance are not significant, there is no support for the remaining hypotheses.

### 5. Discussion

A positive tendency towards the creation of transitive triplets and the negative tendency towards the creation of three-cycles suggest that project creators tend to establish hierarchical network structures. In addition, the positive popularity (alter) effect indicates that prominent project creators receive an increased amount of support from the studied community. Thus, the support among project creators seems to be highly concentrated in a subgroup of popular actors. In crowdfunding networks, this could also promote a concentration of experience and knowledge – especially when a funding relationship might also indicate an increased likelihood for additional support (e.g., advice). Hierarchical network structures such as this can be found in many complex
systems [42]. In this regard, it is interesting to observe that experienced project creators tend to support fewer projects than do inexperienced creators. Similarly, popular creators provide less support than unpopular ones. Thus, we find evidence that project creators do not have a long-term motivation to support others. Once they reach a certain status, their supporting activity diminishes. That experienced and popular actors are too busy with their own projects to find the time and resources necessary to invest in others’ projects may be one explanation. Another may be learning effects: if actor A supports an actor B, B usually receives the amount of money pledged by A. In return, A gets associated with the project and may also be promised to receive access to a tangible result (e.g., a product or a consumable service) once the project is completed. More important, A also gets access to information on B’s project and his project management habits. Thus, A has a chance to observe B and learn from his example. Once A has launched his own projects and gained a certain amount of popularity, he may be less interested in supporting others in order to learn from them. A negative implication of this behavior is that popular and experienced actors may miss important project management and project presentation trends emerging from the crowdfunding community, which could have a potential effect on those actors’ long-term success.

Others have established a preference for reciprocity in crowdfunding networks as well as a positive correlation between reciprocity and project success [58]. In analyzing triadic relationships between actors and their effect on the network level, we extend the scope of previous research on similar networks, which has been limited to the dyadic level of analysis. Our findings confirm a strong preference for the direct reciprocation of project support (i.e., restricted support). Moreover, we observe a negative preference for the indirect reciprocation of project support (i.e., generalized exchange). As described by Bearman [10], restricted exchange systems are often separated into dense subgroups (or clusters) of well-connected individuals. Absent generalized exchange mechanisms, such subgroups form self-sufficient subsystems. Thus, successful strategies and behaviors emerging from one subgroup may remain in that group rather than spreading through the entire network.

Further, Agrawal et al. [5] found that there is no effect of geographic distance between projects and potential supporters on the likelihood of actual project support. In contrast, traditional investors prefer to invest in founders close to them [51]. Moreover, there is evidence that traditional investors show a preference for gender homophily [52]. Our own findings provide additional evidence for the missing effect of geographic distance on project support. Further, our crowdfunding results suggest that there is no evidence of gender homophily among project creators. Hence, compared to traditional investors, project creators in crowdfunding markets show a different behavior in this regard. At the same time, female project creators do receive a higher amount of support from other creators than do male creators. Male project creators have a higher tendency to provide support in general.

The findings above have direct implications for operators of crowdfunding platforms. To avoid losing the experience and knowledge of the most experienced and popular actors at the top of the hierarchy, operators should implement mechanisms to promote the documentation and sharing of knowledge among project creators. For example, project creators could be introduced to each other depending on their level of experience and network position and be invited to establish mentoring relationships. Based on a recommendation algorithm that promotes generalized exchange, the strong hierarchical tendencies could be relaxed.

6. Outlook & Limitations

In our analysis, we found evidence for several mechanisms with a significant influence on the structure of crowdfunding networks. We restricted our analysis in two ways. First, we restricted our analysis to the effect of endogenous and exogenous effects on the structural dynamics of crowdfunding networks. Thus, we did not model the co-evolution of network structure and individual success. While the relationship between the observed mechanisms and performance is highly interesting, we first needed to establish a fundamental understanding of the structural mechanisms themselves. Future research should build upon our findings and consider the interplay between structure and performance. Second, our sample is based on data from a single crowdfunding platform. While this platform is currently the largest of its kind, comparable platforms do exist. Their data could be used to validate our results. Moreover, while there is evidence that attributes of founding teams and their members may have an impact on crowdfunding success [6, 7], we focused on the attributes of the project owners, which are officially designated as such on the corresponding Kickstarter project page. Finally, it is possible that project creators have more than one account on Kickstarter. Using multiple accounts, they could avoid being associated with previous failures or support other projects without revealing their primary identity on the platform. While it is not possible to identify reliably multiple accounts that belong to one
user from an external perspective, the effect on our analysis should be negligible.

7. Conclusion

In this paper, we analyze the mechanisms governing the formation of support relationships in crowdfunding markets, in which actors actively create and fund projects. Our analysis provides evidence for behavioral mechanisms that promote a hierarchical organization of the funding relationships between project creators. Further, we establish that experienced and popular actors tend to fund fewer projects than inexperienced and unpopular actors. In contrast to traditional investment scenarios, we find no evidence for homophily based on gender or geographic distance in crowdfunding. Moreover, we find evidence of gender-related effects, that is, female actors tend to receive more support than do male actors, while male actors tend to provide more support than do female creators. In addition, we establish that the analyzed networks are characterized by restricted exchange; we find no evidence of mechanisms promoting generalized exchange. In summary, we are able to provide insight into the dynamics and evolution of crowdfunding markets, which provide fruitful ground for future research.

8. References
