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Florence Jaouat
TU Berlin, jaouat@tu-berlin.de

Timm Teubner
TU Berlin, teubner@tu-berlin.de

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INFORMAL ALLIANCES IN CROWDFUNDING:
A SOCIAL NETWORK ANALYSIS

Research Paper

Florence Jaouat, TU Berlin, ECDF, Berlin, Germany, jaouat@tu-berlin.de
Timm Teubner, TU Berlin, ECDF, Berlin, Germany, teubner@tu-berlin.de

Abstract

This study explores informal alliances among crowd investors, extending recent work on social networks in (equity) crowdfunding. Beyond formal alliances (such as investment syndicates), informal coordination based on social learning has proven highly relevant to the dynamics and outcomes of financing campaigns. Using data from a leading equity crowdfunding platform, we analyze the informal network structures of investors where ties are based on joint investments over time. We benchmark these networks against random network formation processes and find overwhelming evidence for deliberate network formation. Moreover, we explore how certain investor attributes affect the network’s structure. Specifically, this paper supports the notion that homophily drives social network formation, based on personal attributes such as gender and origin, but also on profile attributes (e.g. badges and images). Within the field of crowdfunding, this is one of the first studies to examine crowd investor networks both from an investor- and a cross-campaign perspective.

Keywords: Crowdfunding, Social Network Analysis, Social Influence.

1 Introduction

Over the past decade, crowdfunding has evolved from a simple means of charitable fundraising to a disruptive financing model that is shifting the distribution and accumulation of capital away from the traditional banking sector (Block et al., 2018). Rooted in the more general concept of crowdsourcing (Howe, 2006; Mollick, 2014), collective financial support to individuals and institutions through hundreds of mainly non-professional investors—the crowd—has rapidly spread and diversified across the internet. While crowdfunding was initially introduced in the non-commercial and art sectors, it has become more popular in entrepreneurial venture financing through its profit-oriented subtype, equity crowdfunding. The latter is expected to experience significant growth in market share, both globally and in Germany (Gierczak et al., 2016).

For most applications of crowdfunding, two-sided digital platforms act as intermediaries and provide the infrastructure for social and financial exchange (Ordanini et al., 2011). A key problem in all types of crowdfunding is information asymmetry: it is difficult for investors to evaluate an opportunity and, once invested, to monitor the founders and ensure that these deliver on their promises (Belleflamme et al., 2014). Unlike shareholders in a stock exchange, crowd investors typically neither hold voting rights in the company, nor do they have extensive experience in which to ground their investment decisions (Vismara, 2018). The crowd’s financial strength stems from the principle of collective action, which has proven to influence investment decision-making (Hornuf and Schwienbacher, 2018). Due to substantial financial stakes in for-profit crowdfunding, uninformed investors in particular refer to the behavior of their peers as a way of evaluating campaign quality or anticipating the likelihood of financing success (Burtch et al., 2016; Zhang and Liu, 2012). In this context, the formation of investment alliances has been identified as a strategy that enables individual investors to pool their strengths, while mitigating the inherent risk of investment decisions. For instance, Agrawal et al.
(2016) highlight the advantages of formal *syndicates* composed of experienced lead investors and “regular” members of the crowd as a means to alleviate information asymmetries and market failure. While investor syndicates are an example of formal and campaign-specific coordination—managed and promoted by the platform operator—investors may also establish and maintain informal ties. Similar to the sharing economy (Teubner et al., forthcoming), public profiles serve as a virtual proof of identity and reputation on crowdfunding platforms, incorporating artifacts such as photos and badges (Klement and Teubner, 2019). Peer visibility engenders social mechanisms like observational learning, which has been extensively studied by the theory of social influence and, more specifically, under the notion of *herding* (Kim and Viswanathan, 2019; Vismara, 2018). Put simply, herding occurs “when an infinite sequence of individuals make an identical decision” (Çelen and Kariv, 2004, p. 484). As investors increasingly use profiles to communicate personal details, not only can they observe and mimic others’ actions but, more importantly, they can coordinate their investments. In this respect, the perception of similar beliefs or demographic features—termed *homophily*—has shown to determine the degree and extent of social ties (McPherson et al., 2001). Examining the structure and antecedents of investor ties is therefore becoming an important subject of inquiry.

Given the practical importance of investor interaction in crowdfunding, there is a remarkable dearth of empirical research on the subject. Grounded in the rationale that the entrepreneurial “inner circle” of friends and family—referred to as *social capital*—determines funding success, previous work has focused on the relationships between founders and investors to explain the structure and dynamics of crowdfunding networks (Ahlers et al., 2015; Brown et al., 2019; Colombo et al., 2015; Skirnevskiy et al., 2017). Following the logic of this academic discourse, social ties in crowdfunding have been understood as venture quality signals, rather than network characteristics with cross-campaign dimensions. Consequently, a number of theoretical questions remain.

By applying a cross-campaign lens to crowdfunding networks, this paper attempts to disentangle investor interaction from the prototypical notion of social capital. Based on a large set of investment data from a leading European equity crowdfunding platform (*Companisto*), we model and analyze a network of around 10,000 active investors from June 2012 to January 2019 to explore informal investment coordination. We expand upon the existing crowdfunding literature, taking an integrative perspective based on the theories and methods from social network analysis. Specifically, we pursue the following research objectives:

- Provide empirical support for the non-random structure of the investor network;
- Present explanations for the formation of investor ties based on homophily.

We hypothesize that investors engage in herding across campaigns, as they invest together multiple times. This paper makes three contributions: First, we present evidence for informal investor coordination based on recurring co-investments on the platform. Specifically, the results indicate that these network structures are far more pronounced than can be explained by coincidence, even when controlling for other variables such as the timing of investment. Second, the data suggest the presence of a densely interconnected core of investors surrounded by a larger periphery of less connected ones. Notably, the network exhibits a large number of one-sided investor relationships indicating a follower–leader pattern. Third, our analysis supports earlier findings suggesting the presence of “similarity bias” (or homophily) in crowdfunding networks. Breaking new ground, we identify a structure of network assortativity across campaigns, which is based on common investor traits (gender, origin) and on the co-presence of investor profile attributes (images, badges). Both strategic IS researchers and crowdfunding practitioners can draw on the presented findings to design, implement, and evaluate features for social interaction in view of (informal) communication and investment coordination, thereby engaging the crowd to invest in ventures on for-profit crowdfunding platforms.

The remainder of the paper is structured as follows. Section 2 provides a review of related work and positions our paper within the theoretical framework of social networks and homophily, before establishing our hypotheses. We then describe the study context, data set, and the methodology employed in Section 3. In Section 4, we present our results. Section 5 concludes with a discussion of implications, limitations, and avenues for future research.
2 Background and Hypotheses

Crowdfunding and Peer Influence — Investment decisions are accompanied by social mechanisms that underpin the structure and dynamics of crowdfunding networks (Horvát et al., 2015). With this in mind, scholars have highlighted the role of social networks and have called for platform infrastructures that enable social interaction (Agrawal et al., 2015; Belleflamme et al., 2015). Although crowdfunding networks are said to form fluid organizations without formal membership criteria (Fehrer and Nenonen, 2019), there is support for a certain structural order and organization within these networks. Previous work has drawn on established concepts from the fields of psychology and sociology, including social obligation (Horvát et al., 2015; Simon et al., 2019; Troise et al., 2020; Zheng et al., 2014), social proof (Bretscheider and Leimeister, 2017; Hong et al., 2018), and social learning (Kim and Viswanathan, 2019; Mohammadi and Shafi, 2018; Vismara, 2018), in order to shed light on the behavioral and structural patterns of crowds. The propensity to financially contribute to a campaign has been explained by the perception of prescribed social norms, reputation and image concerns, as well as the belief that others may have informational advantages.

Grounded in personal ties, social norms are not only said to positively shape entrepreneurial behavior towards investors and reduce moral hazard (Lin and Pursiainen, 2017), but moreover mobilize founders’ inner circle to support a crowdfunding campaign in the critical early stages (Agrawal et al., 2015; Brown et al., 2019; Freedman and Jin, 2017; Lin et al., 2013). Also, having supported other financing campaigns has been shown to positively impact the success of one’s own campaign based on reciprocal commitment (Horvát et al., 2015; Raab et al., 2017). The reciprocity phenomenon is particularly encountered in bipartite networks in which members assume dual roles, namely the role of founder (or borrower) in one situation and investor (or lender) in the next (Horvát et al., 2015).

Investments may not only result from a socially motivated obligation but also from social image or reputation concerns (Bapna, 2019; Bretschneider and Leimeister, 2017; Burtch et al., 2013; Hong et al., 2018). A growing stream of crowdfunding research indicates that popularity information, for instance the aggregated number of investments, as well as electronic word-of-mouth—a form of pseudo-personal communication through social media—serve as “investment magnets” that are able to convince undecided investors to contribute to a campaign (Moritz et al., 2015; Thies et al., 2016). As such, the number of “likes”, “tweets”, and other types of social buzz around a campaign has been shown to serve as key determinants of crowdfunding success in all types of crowdfunding, including donation-based (Hong et al., 2018; Saxton and Wang, 2014), reward-based (Thies et al., 2016), and equity-based crowdfunding (Brown et al., 2019). The attraction effect of these interpersonal cues is based on the belief (and later action) in doing something because others are doing the same. This phenomenon of proving oneself or “saving face” in front of others refers to the aforementioned psychological mechanism of social proof (Sundar, 2008; Thies et al., 2016). It increases with the density of networks and is grounded in the human tendency to build relationships with friends of friends, referred to as embeddedness (Granovetter, 1973).

Extant crowdfunding research has also drawn attention to the tendency of investors to align their decisions with those of their peers—an example of herd behavior (Banerjee, 1992; Bikchandani et al., 1992). Based on this heuristic, later investors may be led to disregard their own knowledge on the investment opportunity at hand, leading to information cascades (Vismara, 2018). In this sense, the timing and size of initial campaign investments have proven critical for funding momentum. Based on observational data from the British equity crowdfunding platforms Seedrs and Crowdcube, previous studies showed that large contributions made in the early stages of a financing campaign increase the likelihood of funding success (Hornuf and Schwienbacher, 2018; Vismara, 2018; Vulkan et al., 2016). Some research indicates that the impact of these “simple” cues on investment behavior, and thus the likelihood of herding, depends on investors’ motivation and/or ability to process “hard” investment facts involving greater cognitive effort and/or time (Allison et al., 2017; Bi et al., 2017; Courtney et al., 2017; Lin and Boh, 2017).

Social Networks in Crowdfunding — The complex social mechanisms mentioned in extant research highlight the importance of relational structures in crowdfunding networks. As a branch of
computational social sciences, social network analysis (SNA) lends itself well to an investigation of these structures in real-world networks (Wasserman and Faust, 1994). It has emerged as a common vehicle used to represent social interaction, such as friendships, with wide applications in entrepreneurial contexts (Greve and Salaff, 2003). Both social network analysis and theory have also proven a valuable framework for studying the evolution, structure, and dynamics of social interaction in crowdfunding (Bellegambe et al., 2019; Fehr and Nenonen, 2019; Hong et al., 2018; Horvát et al., 2015; Vismara, 2016).

Formally, a network can be defined as a relational graph comprised of actors (referred to as nodes) and ties (or edges) that represent the pairwise (dyadic) interactions between them (Wasserman and Faust, 1994). Decades of research have demonstrated that real-world networks differ systematically from random networks in terms of structural properties such as the distribution of ties, clustering, and path lengths. The inhomogeneity of ties is based on a cohesive pattern of subgroups within social networks referred to as the community structure (Girvan and Newman, 2002). A major practical application of SNA is the detection of highly cohesive communities within a network (Girvan and Newman, 2002). Members of a community are shown to be able to reach each other easily, and to weave stronger ties (Borgatti and Everett, 2006). The strength of ties has been associated with joint problem solving and information exchange (Uzzi, 1996). Moreover, it serves as an indicator of trust as the basis for cooperative behavior (Gulati, 1995), enabling social interaction and—we believe—investment transaction. We assume that the formation of investor ties in crowdfunding does not follow a random pattern. Our first hypothesis therefore states:

\[ H_1: \text{Across crowdfunding campaigns, the investor network follows a non-random structure.} \]

**Homophily** — One of the fundamental concepts for explaining the formation of social networks and characterizing its structure is based on similarity (McPherson et al., 2001). “Birds of a feather flock together” is an expression commonly used to describe the human tendency to connect with similar people. This is also referred to as similarity attraction or homophily (McPherson et al., 2001). It is grounded in the theory of social comparison which states that people tend to first compare themselves with and relate to those they perceive as similar (Festinger, 1954). Ties rooted in similarity are more likely to arise and persist over time (Rivera et al., 2010). Homophily is therefore seen as an integral part of building trust by mitigating the conflicts and costs typically associated with building relationships (McPherson et al., 2001; Rivera et al., 2010). This way, it downsizes the social worlds of similar individuals “in a way that has powerful implications for the information they receive, the attitudes they form, and the interactions they experience” (McPherson et al., 2001, p. 415). Similarity can be measured based on value and status: value homophily is grounded in common attitudes, beliefs, and aspirations, while status homophily refers to demographic features such as gender and age (McPherson et al., 2001). As a special case of homophily, the social imperative of physical proximity was exposed as a typical feature of social networks (McPherson et al. 2001).

Given the existence of social ties in crowdfunding networks, a growing stream of crowdfunding research argues that investors tend to support campaigns they identify with based on, for instance, gender (Bapna and Ganco, 2020; Greenberg and Mollick, 2017) or geography (Agrawal et al., 2015; Lin and Viswanathan, 2016; Mollick, 2014). However, not much is known about how investors attract each other. Kim and Viswanathan (2019) suggest that the crowd although inexperienced, is rather sophisticated in its ability to identify and exploit nuanced differences in the informational content of previous (expert) investments. In the same vein, Klement and Teubner (2019) find evidence that “soft” investor cues, such as profile images and expert badges, induce higher campaign funding through the perception of credible peers. Finally, Wick and Ihl (2018) show that herding after experts is stronger among investors who are experts themselves. While the above findings suggest homophily among investors, Mohammadi and Shafi (2018) provide contrary evidence. They find that female investors are more likely to invest in campaigns in which the proportion of male investors is higher, concluding that female investors herd after their male counterparts (Mohammadi and Shafi, 2018).

Homophily between investors is closely connected to herding and the availability of information on other investors. Our data allows us to analyze this behavior because investors are able to provide this
personal information on the platform. Unique to its competitors, the platform facilitates the disclosure of personal information such as name, location, and visual appearance (Klement and Teubner, 2019). This provides a broad basis for comparison with peer investors, which has implications for the formation of ties. We thus hypothesize:

$$H_2: \text{The propensity of a tie between investors increases with attribute similarity (homophily).}$$

3 Data and Methods

3.1 Data Set

Study Context — To evaluate our hypotheses, we employ a large set of investment data from Companisto (www.companisto.com), a leading equity crowdfunding platform for early-stage venture capital based in Germany. At the time of data collection, the platform had coordinated the financing of €63 million from 93,000 registered investors. Capital-seeking start-ups and small and medium-sized enterprises can use the platform. They apply by presenting their business model. After successfully completing the selection process and negotiating the terms and conditions of financing, the company is responsible for creating text and video descriptions to present its business model to potential investors on the platform. A campaign funding goal (in EUR) is defined, which consists of a minimum threshold, the communicated target, and a maximum value. Irrespective of whether it achieves the funding goal, the venture must meet the minimum threshold in order to receive the funds raised by the end of the campaign. Once this threshold has been met, the campaign is classified as “successful” and pays a 15-20% commission to the platform.

Past and current funding campaigns are summarized in chronological order on the platform. By clicking on a campaign, a potential investor is directed to the campaign page. This page contains a textual description, a cover picture, a pitch video, and a financial summary sheet. Another subpage contains the investment history for the respective campaign, displaying every single investment in a table. This information includes the size and date of the investment, the exact sequence of previous and later investments, and the investors. Investors are represented by their username, a rank, their city and country of residence, a profile picture (i.e., either a custom uploaded photo or default avatar), and, in some cases, a platform-issued badge. Apart from these implicit cues, they have no means of (direct) communication. Figure 1 shows a typical excerpt of investments with these features (left) and an overview of investor cues on selected equity crowdfunding platforms in Germany.

![Figure 1. Excerpt of a campaign investment list (left) and overview of investor cues (right).](image)

Data Collection — Using a web crawler to query the platform, we collected public investment data for all 101 financing campaigns from June 8, 2012 to January 30, 2019. Of these, 94 had been

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1 Badges denote membership to a status group—the so-called Business Club, which is associated with various privileges.
successfully funded. Our initial data set comprises 68,158 individual investments across the 101 campaigns. In addition to various kinds of campaign and investor information, we retrieved date stamps of the individual investments and the precise order in which these occurred. The data were collected in March 2019.

**Data Preparation** — We first cleaned the raw data, removing transactions outside the official campaign phase, leaving us with 67,839 observations. Next, we created dummy variables for profile picture (1 = individual; 0 = default) and badge (1 = present; 0 = not present). Moreover, we inferred investors’ gender from their first names (Peters, 2020), which analyzes the frequency and common patterns of names based on the Google database (1 = female; 0 = male). This is an increasingly popular method (Karimi et al., 2016; Mohammadi and Shafi, 2018), allowing us to classify 99.7% of all investments as either belonging to male (89.5%) or female (10.2%) investors. To maintain the precise order in which investments occurred during data analysis, we added a unique ID to each investment in the list, sorting them from most to least recent. We computed a normalized time variable for each investment to account for the variations in campaign length. This variable represents the elapsed campaign time, where 0 indicates the first day and 1 represents the final day of the campaign.

Since investors on the platform cannot necessarily be identified by a unique ID, we developed a means of identification by combining three features available for each observation: username, origin, and rank. For example, an investment made by “Thomas” (i.e., the most frequent name in the data set) based in “Berlin” (i.e., the most frequent city in the data set), ranked at position “7461”, would be assigned to the investor “Thomas from Berlin (7461)”. We believe that the combination of these three profile attributes serves to distinguish between individual investors given the consistency of this modified data set. Based on the assumption that several observations associated with an investor are linked to a single account, we have reconstructed each investor’s portfolio by grouping investments by investor. To stay with the previous example: Thomas from Berlin (7461) invested a total volume of €1,700 across 11 financing campaigns. We identified 19,750 investors using this approach.²

**Descriptive Statistics** — The average total investment volume per investor is €2,092 (min.: €4; median: €500; max.: €150,000), distributed across 3.4 campaigns (min: 1; median: 2; max: 105). Note that typically, there is only one single investment per investor and campaign. Overall, 16.8% of investors are female, accounting for 10.2% of all investments and 9.4% of the overall investment volume. Moreover, 11.8% of investors have a custom profile picture, 7.0% of investors have a badge, and 86.3% of investors are based in Germany. The majority of campaigns (93.1%) were successful. Campaigns had an average of 670 investors (min: 45; max: 2,251) and an average duration of 120 days (min: 1; max: 370). Investments were concentrated towards the first quarter of the campaign’s timespan. This is in line with previous findings on the dynamics of crowdfunding campaigns (Hornuf and Schwienbacher, 2018).

### 3.2 Network Generation

**Network Model** — Networks can be analyzed on different levels: the individual, the dyad, and the entire network. The atomic unit of network structure is the dyad, that is, a pair of nodes connected by an edge. We focus on dyads because the focal points in this research are the relational and assortative structures of investor networks. In this context, we define a dyad as a pair of investors connected by at least τ (tau) investments to the same project on the same day. For instance, assuming a threshold level of τ = 2, investors A and B would be considered connected if both had invested in project X on June 25, 2018 as well as in project Y on October 6, 2019. Using this, we generate the set of dyads. The number of joint investments (i.e., same-day same-project investments) for each dyad is represented as the edge weight, that is, the strength of their tie. Note that the network is undirected.

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² This represents the total number of **active** investors as opposed to the officially reported number of 93,000 **registered** users, indicating a 21% activity rate on the platform.
Applying the lowest possible threshold ($\tau = 1$) yields a total of 1.05 million dyads among 19,570 unique investors. However, this network is not very meaningful as these co-investments are—by design—not distinguishable from random co-investments. The network becomes more meaningful the higher the required threshold for same-day same-project co-investments is set. Note that the network also becomes smaller with increasing values of tau. Where investors have at least two co-investments, the network comprises 736,166 connections among 9,940 investors.

**Network Visualization** — In Figure 2, we consider depictions of different network subsets for selected values of tau (1, 6, 10). Investors are modeled as nodes. The node size represents an investor’s total volume of investments. Co-investment relations between investors are represented as edges. The number of co-investments is represented by the edge width. The Fruchterman-Reingold layout was used for all images (R igraph-library; Csardi and Nepusz, 2006; Fruchterman and Reingold, 1991). As can be seen in Figure 2, investors are almost perfectly connected for low thresholds, and the number of connections decreases sharply for higher required frequencies of co-investments. For example, only 35 investors have made joint (i.e. same-day) investments across ten campaigns.

![Figure 2](image.png)

*Figure 2. Investor networks with minimum tie strength $\tau = 1$ (2,032 connected nodes, 116,185 edges), $\tau = 6$ (84 nodes, 518 edges), and $\tau = 10$ (35 connected nodes, 111 edges).*

### 4 Network Analysis and Results

In the following, we investigate the structure of the investor networks, benchmark them against random networks, and discuss potential explanations for the underlying formative mechanisms.

#### 4.1 Non-Random Network Formation

Randomization allows us to examine whether the formation of ties between investors can be explained by chance or, as hypothesized, whether investor ties are the result of informal coordination. To test our first hypothesis ($H_1$), we compare the properties of the investor network to a benchmark of randomly generated networks. We retain the number of investors, their investments, and the density of the original network (i.e., the proportion of existing edges against all possible edges). By manipulating the timing of investments, we create investor connections that do not exist in the original network. In an initial, lower benchmark, investments are distributed over the campaign period with equal probability, that is, each day of a campaign is equally likely (uniform network). We then model a higher benchmark of random networks given that crowd investments are known to accumulate at the beginning of a funding campaign (Hornuf and Schwienbacher, 2018). In this higher benchmark investments are assigned to days according to the actual temporal distribution for each campaign using the computed normalized time variable (informed network). For each of our random networks (i.e., uniform and informed), we perform 30 simulations and compute average scores for the respective number of nodes and edges along with the standard error (SE) for a set of minimum edge weights $\tau$ ($1 \leq \tau \leq 20$). Table 1 summarizes the values for the most relevant edge weights ($1 \leq \tau \leq 7$).
The edge weight is the strength of a relationship built on the history of joint campaign investments. For instance, a threshold \( \tau \geq 5 \) indicates that two investors invested in at least five financing campaigns on the same day. Based on the assumption that investors preferentially choose other investors to coordinate with, we expect the number of observed connections to exceed the number of randomly generated connections for increasing levels of \( \tau \). Figure 3 shows the number of nodes (left) and edges (right) for the actual investor network (red) and the two random benchmark networks with informed (black) and uniform (grey) distributions.

As shown in Figure 3, the observed numbers of both nodes and edges are several orders of magnitude larger than can be explained by random assignment. Note that the y-axes are log-scaled. For instance, for \( \tau \geq 5 \), we observe an original network with 600 nodes and 8,003 edges. A random generation process, on the other hand, yields 78 nodes (SE = 1.92) connected by 75 edges (SE = 2.87) in the informed distribution. This difference is statistically significant (T-test, \( p < 0.001 \)). The same holds for all thresholds \( \tau \geq 1 \).

Comparing the size of our original investor network to those of the random benchmarks strongly suggests a non-random formation pattern based on joint campaign investments. This provides support for our first hypothesis (H1). Next, we study the structure of our investor network in more detail.

### 4.2 Network Topology

The structural arrangement of nodes and edges—the so-called topology—plays an important role in characterizing a network. In fact, nodes’ overall position in the network may explain their dependence on others as well as their commitment and performance. Network centrality measures are used to uncover the roles of different actors within a network and quantify their capacity to influence, or be influenced by other actors (Borgatti and Everett, 2006). These measures summarize the extent of dyadic cohesion—that is, the connectedness and “togetherness”—of each node. For the purpose of characterizing and comparing the interactions found in real-world networks, a number of measures have been developed, each of them useful in different contexts. Aggregating these node centralities at the entire network level allows us to compare different networks with each other. Absolute (i.e., local)
and relative (i.e., global) measures of structural centrality are analyzed in combination because they cover different conceptualizations of centrality (Freeman, 1978). We use three measures of interconnectivity to develop a more complete perspective of this network: degree, mean distance, and transitivity.

We apply random network graph techniques in order to infer meaning and context from these measures. Generating random graphs is an important method for investigating how likely or unlikely network structures are to occur given certain properties of the original network. A simple random network graph—such as the classical random graph model of Erdős and Rényi (1959)—is one in which two nodes are connected with a constant and random probability, while retaining the density of the real-world network. We simulate 100 random networks with the approximate same density and number of nodes as our actual network. Table 2 summarizes the centrality measures for the investor network (τ ≥ 1) and the Erdős-Rényi network, along with the percentiles and standard deviations (SD).

<table>
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Table 2. Erdős-Rényi network randomization (n = 100).

**Degree** — Degree centrality indicates the number of direct connections each node has to other nodes. Taken as a node’s activity level, this measure captures its importance, influence, or popularity (Freeman, 1978). In line with previous research (Borgatti et al., 1998), we assume that an investor having many direct connections must be at the center of communication—or coordination. Investors with a small number of direct links, on the other hand, are expected to play a peripheral role in the network. At the local centrality level, investors have established connections to an average of 148 other investors (min: 1; max: 2,688); this value is, of course, the same for the random network. The original network contains a vast spectrum of node degrees with an inhomogeneous distribution compared to the Erdős-Rényi network (Table 2). At the global level, degree centralization is defined as the ratio of the sum of node degree differences to the maximum possible sum of node degree differences within a network. In simple terms, the measure reflects the relative dominance of one single node in the network (Freeman, 1978). The greater the degree centralization, the more likely a single node is to be central and remaining nodes to be considerably less central. Degree centralization is therefore highest for networks with one node having a maximum degree and all remaining nodes having a minimum degree. This is the case for a star network. Similarly, the degree centralization is lowest for networks where all nodes have a similar number of connections, as is the case for a circle network (Freeman, 1978). The original network has a higher degree centralization (0.26) compared to the Erdős-Rényi network (0.01; SD: <0.01). In line with the core-periphery pattern of social networks, these values suggest the existence of a densely connected core of investors surrounded by a periphery of less interconnected investors. To put it boldly, some investors might not only be considered more active, but also more influential than others.

**Distance** — Mean distance (or average path length) is another common quantifier for the overall interconnectivity of a network. It is a measure of the mean lengths of the shortest connections between all dyads in the network, with the number of edges representing the geodesic distance. Nodes that are connected to each other directly have a distance of 1. With every additional node in between them, the distance increases. The investor network’s mean distance (2.48) exceeds the mean distance of the Erdős-Rényi network significantly (+0.39; SD: <0.01), as shown in Table 2. The relatively large mean distance indicates that the investor network is not a “small world” in that investors appear to have preferentially chosen some investors over others to coordinate with. Notably, as the edge weight
increases, so does the mean distance in the investor network. This suggests that the network is breaking up into smaller communities whose members—sharing a common history of serial investments—can easily reach each other while remaining at a relative distance to non-community members (Borgatti and Everett, 2006).

**Transitivity** — Transitivity (or the clustering coefficient) is the proportion of all possible connections among nodes’ neighbors that exist within a network. It indicates nodes’ tendency towards cluster formation. For the original network, the transitivity is 0.544 (min: 0; median: 0.52; max: 1), that is, 54.4% of nodes form so-called “closed triplets” (Table 2). This stands in stark contrast to the Erdős-Rényi random networks, where only 1.5% of nodes form closed triplets (SD: <0.01), and points to the existence of clusters within the investor network.

The randomization tests performed (degree, distance and transitivity) strongly suggest that this is a non-random investor network composed of several cohesive subgroups. In the following, we set out to explain these preliminary findings.

### 4.3 Network Symmetry and Homophily

Although topology is an important aspect of complex networks, it cannot on its own characterize and compare the extensive and diverse interactions between nodes. An important question to be addressed is why the investor network could have emerged in the first place. We start by examining investor interactions in more detail.

**Reciprocity** — The analysis has thus far focused on the undirected investor network. However, real-world relationships are not symmetrical *per se*. To account for this, we model a directed network graph in which the arrow connecting each pair of investors points to the “leader”, that is, the one who invests first. This allows us to make statements about reciprocity. With an overall reciprocity of 0.11 at the network level, the majority of relations seem to be unilateral, where followers follow leaders.

**Assortativity** — As demonstrated above, the investor network does not emerge randomly and it is divided into sub-communities. Members of a community are not only shown to exhibit stronger links, they are also thought to share similar characteristics and roles within the network (Fortunato, 2010; Rivera et al., 2010). Hence, apart from structural features, a node’s position can be thought of as the result of investors’ attributes. In graph theoretical terms, assortativity refers to the notion that nodes with similar attributes are more likely to connect than dissimilar nodes (Rivera et al., 2010). To evaluate our second hypothesis (H$_2$), that is, whether investors preferentially attach to other investors with similar attributes, we take a two-step approach. Firstly, we compare the *de facto* share of same-attribute connections within the investor network against the *expected* share of such relations based on the distribution of attributes (origin, gender, image, badge). Table 3 shows the expected (EXP) probability for investors with same attributes to form a connection versus the actual (ACT) rate of investor dyads with this attribute—along with the 95% confidence interval (95CI) for different edge weights (1 ≤ τ ≤ 5). All values indicate percentages.

<table>
<thead>
<tr>
<th>Same Attribute</th>
<th>Edge Weight (τ)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>EXP</td>
</tr>
<tr>
<td>Gender</td>
<td>79.34</td>
</tr>
<tr>
<td>Image</td>
<td>2.03</td>
</tr>
<tr>
<td>Badge</td>
<td>1.35</td>
</tr>
</tbody>
</table>

*Table 3. Expected (EXP) and actual (ACT) rates of same-attribute dyads.*

As shown in Table 3, investors’ tendency to establish ties increases if they have the same origin (+1.63%), same gender (+10.26%), or both have an image (+5.99%), or badge (+1.55%). These values increase with higher edge weights. For instance, with τ ≥ 10 (i.e., at least 10 joint campaign
investments), the data show 10.86% of dyads with same origin (+2.87%; CI: 1.75), 88.99% with same gender (+9.65%; CI: 1.7), 9.19% both having a customized profile picture (+7.16%; CI: 1.63), and 4.22% both having a badge (+2.87%; CI: 1.13). Note that the analysis of local assortativity was performed at the level of the 16 German Länder (i.e., federal states).

Next, we consider investor dyad attribute constellations as explanatory variables for predicting whether or not these investors form ties. We generated a set of all possible undirected investor connections \((N = (n^2-n)/2 = 49,396,830; \text{with } n = 9,940 \text{ investors})\). Out of these connections, only 1.8% exist in the actual network. For each possible investor dyad, the dependent binary variable represents whether a tie exists (1), or not (0). As explanatory variables, we consider whether a pair of investors shares the same origin, same gender, a profile picture, or a badge. Table 4 summarizes the results of the logistic regression including the estimates, the standard error (SE), z-statistic, and \(p\)-values for the attributes (origin, gender, image, badge). Based on the model, we find the coefficients to significantly correlate with the dependent variable \((p<0.001)\). The formation of ties can therefore be predicted by the assortative structure of investor dyads.

| Coefficient            | Estimate | SE   | z value  | Pr(>|z|) |
|------------------------|----------|------|----------|----------|
| (Intercept)            | -.14     | .003 | -1520.80 | <.001    |
| Same Origin            | .11      | .004 | 30.37    | <.001    |
| Same Gender            | .21      | .003 | 68.67    | <.001    |
| Both Image             | .71      | .006 | 121.30   | <.001    |
| Both Badge             | .89      | .006 | 133.53   | <.001    |

Table 4. Logistic regression results on dyadic assortativity.

In conclusion, the data provide evidence that the attributes investigated in investor profiles serve to explain the formation and strength of investor ties formed across crowdfunding campaigns. Regarding our assumptions with respect to homophily among investors, overall the results support our second hypothesis \((H_2)\).

5 Discussion

Motivated by the recent expansion of crowdfunding, this paper set out to explore the role of informal coordination among investors. Taken together, our analysis confirms the existence of investor networks formed through campaign investments on Companisto, a leading German equity crowdfunding platform. The data suggest that one of the underlying mechanisms of how investors connect with peers—that is, to copy their investments (or “copy-invest”)—is homophily.

5.1 Theoretical Implications

This study adds to the literature on social influence in (equity) crowdfunding by providing evidence of deliberate cross-campaign ties between investors. The results show, first, that crowdfunding networks are not a set of “frozen” interactions. By tracking investors across campaigns, we were able to witness relationships evolving over time through repeated investments. Some investor pairs are even shown to have repeatedly co-invested in 36 distinct crowdfunding campaigns, always on the same day. These results underline the importance of informal coordination among investors. Thus far, the impact of peer investor ties across crowdfunding campaigns is under-researched. By analyzing data from two French platforms for reward-based crowdfunding, Belleflamme et al. (2019) show that recurrent investors are an important source of positive funding dynamics across campaigns. They find that these investors encourage future funding by initiating social learning about the existence and quality of campaigns among other investors (Belleflamme et al., 2019). Extending previous findings, we suggest that recurrent investors can not only encourage novice investors but moreover other recurrent investors to participate in campaigns.
Second, our results provide a preliminary insight into the relational structure of crowdfunding networks. When breaking down co-investments into a leader–follower structure, the data suggest that investor ties are not mutual. The network appears to have a leader–follower pattern in which a minority of investors are followed by a mass of investors and, thus, are likely to demonstrate influence. This observation indicates herding at a platform level. This result conflicts with the findings of Belleflamme et al. (2019) on cross-campaign funding dynamics, who suggest that recurrent investors tend to invest independently of others as they are active in the early stages of a campaign. This conclusion seems premature—just because something is not immediately visible to the researcher's eye does not mean it is not there. The coordination we suggest may have occurred informally within or outside the public funding arena, and therefore would have been invisible to third-party observers.

Third, to position our paper within the active debate on homophily in crowdfunding, the results suggest the assortative structure of investor networks based on investor attributes. Investors tend to form alliances with similar investors, based not only on personal traits (i.e., gender and origin) but, interestingly, also on profile attributes (i.e., the availability of an image and/or a badge). This extends previous work on homophily, which has largely centered around the relationship between founders and investors, arguing that investors tend to support campaigns they identify with based on, for instance, gender (Bapna and Ganco, 2020; Greenberg and Mollick, 2017; Horvát et al., 2015) or geography (Agrawal et al., 2015; Lin and Viswanathan, 2016; Mollick, 2014). Moreover, our findings are in line with extant crowdfunding literature on herd behavior (Kim and Viswanathan, 2019; Klement and Teubner, 2019; Wick and Ihl, 2018), except for Mohammadi and Shafi (2018). We suggest that this study’s results serve as a motivation to explore social interaction in crowdfunding at a cross-campaign level.

5.2 Practical Implications

Companisto has gained tremendous momentum since its inception in 2012. The number of active crowd investors grew from around 1,300 to 20,000 and the number of investor connections from 24,000 to 1 million by 2019. Despite well-researched social mechanisms in crowdfunding, the platform has failed to facilitate social interaction between its users, who were unable to exchange direct messages, follow each other, or receive notifications of each other’s activities by the time of data collection. Our analysis has shown that across campaigns, investor ties are (1) non-random, (2) mostly unilateral, and (3) based on similarity. From these results, we can conclude that there is a densely interconnected core of investors—whether or not platforms actively encourage social interaction. The data provide evidence of informal exchange among investors even though they are not able to communicate directly on the platform. As a managerial implication for platform operators, we recommend, first, facilitating direct communication to stimulate investment activity. This ultimately helps campaigns to meet their funding goals. Second, we propose leveraging the wisdom of popular investors. Similarly to the increasing use of featured lead investors, platforms could take advantage of less formal leader–follower mechanisms by promoting funding campaigns through well-connected “influencers”. The latter may then activate their own social capital to invest in a given opportunity. Assuming that active investors are also better informed (Agrawal et al., 2016), this may positively impact the decisions taken by less experienced members of the crowd. Third, homophily among investors has so far been an underutilized asset on platforms; most of them do not list their investors publicly. To leverage the natural tendency of individuals to associate with similar people, platform operators should introduce public profiles with personal information, presenting relevant activity, skills, and interests. This could not only allow investors to identify like-minded peers to coordinate with, but also enable founders to exploit investor expertise, similar to the “smart capital” provided by business angels.

Interestingly, Companisto has implemented some of the above recommendations in the meantime. It has launched the "Investment Club," which allows investors to create personal profiles, link to their profiles on other professional networking sites (e.g. LinkedIn), and contact each other as well as
entrepreneurs seeking capital in private. In this way, verified investors can connect with each other, assess each other's expertise, offer support to entrepreneurs, and indicate their investment interests to receive tailored offers. Currently, there is no other platform in the German market for equity crowdfunding that enables direct social interaction. Common features on platforms in this market are limited to popularity information (e.g. number of previous investors) and investor discussion forums where investors can post comments anonymously or under their usernames to engage with entrepreneurs (see Figure 1 on the right). The small number of best practice examples brings us to conclude that the road to social interaction on equity crowdfunding platforms is a long one.

5.3 Limitations and Future Research
The present paper has several limitations that constrain the scope of its interpretability. Two major limitations concern generalizability and methodology. First, the sample is based on a single equity crowdfunding platform. The results may therefore not generalize to other platforms with different campaign specifications, legal frameworks, or design features. Second, personal information shared on the platform is not verified, that is, investors may use false names, cities, or photos. Although we were able to identify investors based on the data obtained, there is still some uncertainty regarding this assignment of online profiles and actual investors (e.g. due to changing names or duplicates). In addition, we cannot verify whether investors knew each other personally. Third, we do not explore the psychology and behavioral mechanisms leading to the coordination patterns observed—particularly, whether these are the result of conscious processes. We defined similarity from a research perspective, namely as the co-presence of profile attributes among investor dyads. Whether investors in our sample perceived similarity/dissimilarity based on the attributes studied remains unanswered. Fourth, we cannot rule out interactions with the type of campaigns. The observed homophily between investors could be partially explained by industry or funding volume. For instance, female investors are more prevalent in categories such as food (12.7%) and lifestyle (10.9%) than tech projects (7.9%).

Finally, while we acknowledge the practical relevance of the current research focus on the determinants of crowdfunding success, we believe that concentrating solely on the relationship between investors and capital seekers does not sufficiently explain the functioning of the fast-growing crowdfunding industry or predict its development. A key but often overlooked reason is that the crowd is not a homogenous entity, but a community of temporary common interest. The financing of a venture in exchange for profit participation is a primary motivation. We encourage future research to apply a cross-campaign lens on crowdfunding networks and reconsider previous research findings to provide a more holistic view of this market. As a starting point, we suggest gaining more insight into (1) the structural features of highly networked subgroups of investors, (2) the role of information disclosure and profile attributes in the formation of ties, and (3) how the above groups interact with the rest of the crowd, in terms of investment timing, volume, and information exchange. Further questions include whether informal coordination is the result of conscious behavioral processes, and whether these, in turn, lead to better investment decisions. Also, whether new members rely on more experienced users in their decision-making is a question we leave to future research.

6 Conclusion
We set out to explore investor networks in equity crowdfunding. We took a snapshot of seven years of investment activity on a leading European equity crowdfunding platform. Based on a large data set of crawled investments, we modeled a network of investors at the dyad level, where their connections were based on the history of joint campaign investments made on the same day. Applying the theory of social networks and homophily, and adopting network randomization techniques, we investigated the structural properties of investor ties formed across financing campaigns. We investigated whether the investor network was the result of non-random formation processes, and whether it could be predicted based on attribute similarity. We found support for both hypotheses. As one of the first studies on this subject, our preliminary results contribute to the nascent literature on cross-campaign dynamics and homophily among investors in equity crowdfunding.
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