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The clientele effects in equity crowdfunding: A complex network analysis

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ABSTRACT

The study develops an original interdisciplinary approach, leveraging complex networks through which it identifies groups of investors and projects in equity crowdfunding, investigates whether clientele effects arise resulting in specific investor-entrepreneur matching, and explores which investor-entrepreneur combinations can lead to the emergence of collective behaviors. Data about campaigns and investors are gathered from Crowdcube to identify investors and company types that populated this leading UK platform during its early years (2011–2016). Results show that the clientele effect exists only between specific investors and project types: serial investors are attracted to innovative companies, whereas high-value and small investors, representing the largest group in the crowd, prefer mature companies in the consumer product industry. Moreover, the study reveals that information exchange in certain matching drives the clientele effect, resulting in collective behavior on specific segments: small investors engage in collective behaviors only when targeting high-tech innovative companies. These findings provide a new view on the clientele effect in equity crowdfunding platforms and the financing of innovative companies.

1. Introduction

Equity crowdfunding has emerged in recent years as an online alternative and complementary financing channel, facilitating capital supply to innovative new ventures and creating new ways for individuals to invest (Block et al., 2018; Pollack et al., 2021; Vismara, 2016). Through equity crowdfunding platforms (CFPs), entrepreneurs can make an open call offering a predetermined percentage of equity shares to a large base of individuals (Butticè and Vismara, 2022). Therefore, equity CFPs have a pivotal role in creating a lively financial ecosystem, through signaling innovative companies to the market, attracting different groups of investors, and creating value by enabling matching between investors and entrepreneurs (Belleflamme et al., 2015; Schwienbacher, 2019). As evidenced by previous studies (Brown et al., 2019; Lehner and Harrer, 2019), CFPs have peculiar characteristics, being open networks with no formal inclusion or exclusion criteria, comprising non-hierarchically organized social and business ties. There is, consequently, heterogeneity in both the types of proposed entrepreneurial projects and the types of investors constituting the crowd active on the platform.

Considering 81 funded campaigns and 8559 investments made – from 2011 to 2016 - by 5995 unique investors on one of Europe's leading equity CFPs platforms "Crowdcube", the objectives of this study are threefold: firstly, to categorize investors' and projects' types in equity crowdfunding; secondly, to investigate the emergence of clientele effects concerning specific types of entrepreneurial opportunities; and thirdly, to determine whether the clientele effect, in part driven by dynamics of information exchanges, such as it occurs in peer-to-peer interactions, is observable peculiarly in specific investor-entrepreneur matching.

Regarding the first point, seminal articles in equity crowdfunding have focused on factors explaining the success of crowdfunding campaigns (e.g., Ahlers et al., 2015; Lukkarinen et al., 2016; Mahmood et al., 2019; Piva and Rossi-Lamastra, 2018; Ralcheva and Roosenboom, 2016; Vismara, 2016b), empirically exploring CFPs from a mainly one-sided perspective—either the role of company signals in attracting investors (e.g., Ahlers et al., 2015; Kleinert et al., 2021; Lukkarinen et al., 2016; Vismara, 2016) or different investors' responses to a specific signal (e.g., Ferretti et al., 2021; Guenther et al., 2018; Shafi, 2021). With few exceptions (Estrin et al., 2021; Thies et al., 2018), only theoretical studies have taken a more comprehensive view encompassing both sides of the CFP, such as investor–entrepreneur combination (Gal-Or et al., 2019; Lehner and Harrer, 2019). The first contribution of this work lies in

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identifying the various groups of investors and projects within the equity crowdfunding platform, thereby addressing the previously limited attention devoted to examining investment matching in the context of a heterogeneous crowd choosing among different types of entrepreneurial projects (Pollack et al., 2021).

Building on this work, we note that the investor–entrepreneur combination in CFP is akin to the `clientele effect' developed in the financial literature —venture market segmentation sustained by investors focused on sub-sets of the investment universe according to their risk-return preferences (Barberis and Shleifer, 2003). While the clientele effect in the stock market is based on well-established characteristics (e.g., older investors preferring dividend-paying stocks for cashflow purposes or retail investors tending to hold local stocks), less is known about whether the companies' and investors' characteristics affect the amount invested in the CFP context. Thus, the second contribution of this paper is to explore the clientele effect in CFPs, examining whether investment matching exists between particular investor and project types. This can help companies tune the communication and launch strategies to make investors more likely to invest in them.

Thirdly, to thoroughly investigate the clientele effect in the context of heterogeneous actors on both sides of a CFP, two perspectives must be considered: individual and collective. At the individual level, the clientele effect is purely driven by investors and project characteristics (i.e., homophily or similarity). From this perspective, the clientele effect derives from the interaction of i.) investors' characteristics (i.e., retail or institutional) and their risk-return appetite, and ii.) companies' signals that are generated through the information they produce. At the collective level, the clientele effect is driven by information exchange (i.e., peer-to-peer effects, information cascades, rational or irrational herding). Thus, investors' homophily, psychological or information dynamics, such as peer-to-peer information exchanges, observing others' choices (i.e., herding), and following common information sources, may lead a group of investors to select the same companies within a specific segment. Therefore, regardless of the precise nature of the underlying mechanism that our analysis cannot discern due to data limitation, collective investment behaviors represent one of the elements determining the clientele effect.

Despite their importance, concerning this third level of analysis, few studies have addressed the formation of collective investment behaviors. According to Park and Burgess (1921, p. 866), collective behavior "is the behavior of individuals under the influence of an impulse that is common and collective". An example of collective behavior in the financial context is the historic 'Tulip Mania' when the irrational exuberance of investors pushed them to invest in one particular flower or the more recent Dot.com and Cryptocurrency and NFT Mania (Reinhart and Rogoff, 2009). Two additional elements are crucial for our research design to complement the broader definition of `collective behaviors' of Park and Burgess (1921, p. 866). First, individuals are more likely to develop collective behavior through direct and intentional information exchanges and/or exposure to common stimuli and information sources (Del Re, 2013). Second, complex system research shows that many economic and financial systems consist of interacting parts, or groups (Arthur, 2021). In many cases, some of the agents populating the system are observed to significantly converge their activities towards the same targets, thus forming one or more groups with specific collective behaviors (Newman, 2011). Any system may contain multiple such groups, each one converging around its targets.[1] Our dataset enables an examination of whether distinct investor segments not only pursue specific project categories but also consistently target particular firms within those categories. Thus, recognizing the need for further exploration in this field, our third significant contribution offers fresh insights to more comprehensively understand the investor-entrepreneur pairings that may give rise to collective behavior patterns. These collective behaviors are worth studying as they might affect platform continuity and venture financing since groups of investors can significantly concentrate or limit their investments in the same companies.

To drive our threefold aims, the following research question is stated:

Which entrepreneurial projects' characteristics and investors' behavior, individually and collectively, contribute to the emergence of clientele effect in an equity CFP?

As discussed, this research question first demands the identification of investors and project groups based on their characteristics and signals. In this vein, we develop a cluster analysis. Then, after identifying investors' and project types, a methodology capable of (i) simultaneously addressing the diverse characteristics of both investors and companies and (ii) effectively managing the interdependence among investors' choices is needed. The latter interact in numerous complex ways, many of which may be influenced by factors we cannot observe. Consequently, standard statistical techniques like regression models, assuming independent observations, are not applicable (Wisniewski and Rawlings, 1990). Our primary goal in treating the CFP as a bipartite network connecting investors with companies seeking investment is to investigate whether certain categories of companies attract disproportionately larger investments from specific investor categories beyond what would be expected by random chance. For this purpose, we employ the 'configuration model' (Molloy and Reed, 1995), a complex network technique not previously implemented in crowdfunding research. This method involves generating null networks that preserve the same overall investment amount for each investor while randomizing the specific parties involved in the investments. This approach enables us to identify our second objective, clientele effect, i.e., which investor types have significant propensities to invest in particular categories of companies.

For the third part of this study, we generate a second set of null networks also based on the configuration model. However, we now add constraints that control for investment matching, so this second set of null networks represents a more proper term of comparison to test whether investors of particular types form separate groups, each of which significantly concentrates its investments in the same companies. In order to investigate and detect the presence of multiple groups in a network, like the one of the CFP, community detection analysis is the established statistical technique (Girvan and Newman, 2002). Indeed, community detection analysis naturally uncovers the results of collective behaviors, unlike standard regression analysis, which is typically aimed at estimating impacts (or elaborating predictions) at an individual level. If significant convergence of investments is observed within specific groups identified through community detection, collective behaviors are revealed.[2]

The Crowdcude data employed in this study covers the initial years of the platform's activity, aiming to identify which types of investors and companies started to populate the CFP network. We use cluster analysis to identify different segments within investors and projects to reduce actors' heterogeneity. Companies are categorized by their signals during investment campaigns, while investors are grouped based on their investment behavior. Then, we use network theory to analyze investment matching between investor and project segments, whereas network links represent investment decisions weighted by the invested amount. The result of our second part of the investigation reveals that serial investors

[1] The presence of groups with collective behavior has nothing to do with the presence of different types of investors. Indeed, the formation of groups can be observed even among investors having the same features.

[2] The null networks belonging to the second model are built so to preserve the observed investment preferences of each actor in terms of the amount invested by company type. In these networks, randomness no longer pertains to the selection of company types by investors. Instead, given fixed investments in specific company types as observed in the original CFP, only the choice of which specific companies to invest in (among those of a same type) is stochastic.

(investing small amounts in many companies) significantly prefer innovative ventures. By contrast, small investors make smaller than expected investments in these companies, preferring projects in the consumer product sector that are highly informative to the market (i.e., well-established companies). In the third part of this study, results reveal that only small investors show significant collective behaviors in their investment decisions, specifically targeting innovative start-ups.

The study has implications for both academics and practitioners, substantially contributing to the crowdfunding literature. First, while the role of companies' signals and crowd characteristics have been considered independently, this study evidences that simultaneously considering both sides of the market yields new insights into detecting different groups of investors and projects in equity crowdfunding. Secondly, it provides evidence of investment matching only for certain combinations, i.e., when specific types of investors invest in specific types of segment. In particular, our results elucidate the importance of industry for crowd investors, pinpointing the relevance of high-tech projects (Chan and Parhankangas, 2017; Le Pendeven and Schwienbacher, 2023; Johan and Zhang, 2021; Jung et al., 2022). These findings make a valuable contribution to the literature on crowd investors (following Ferretti et al., 2021; Shafi, 2021) and on the clientele effect in CFP by identifying segment structures in investment matching—a previously uninvestigated aspect. Thirdly, the results regarding collective behaviors allow a further understanding of clientele effect, and how this is related to money allocation by specific groups of investors. We demonstrate that, when some types of investors are targeting certain types of companies, their final investment selection cannot be considered the outcome of an individual random process. Although the literature already discusses the presence of collective behaviors in finance (Li et al., 2016; Dal'Maso Peron and Rodrigues, 2011; Stosic et al., 2018), but as a novelty, our work is the first to consider whether actors' heterogeneity shapes its formation. Finally, we introduce a complex network approach not previously applied to study CFPs. This paves the way for an essential shift: from an analytical, linear perspective that decomposes CFPs into cause–effect relationships between entrepreneurial projects and investor behavior to a non-linear view in which interdependence among investors and between investors and entrepreneurs influences investment matching. Indeed, this new research approach can be extended to entrepreneurial finance in general and not only to CFPs.

The paper is structured as follows. Section 2 presents the theoretical background and hypotheses. Section 3 introduces the dataset and methods deployed. Results from applying these methodologies are reported in Section 4, while their discussion and implications for entrepreneurs and platform managers are addressed in Section 5.

2. Literature background and hypotheses development

2.1. Literature background

In behavioral finance, the clientele effect concerns the intention of a group of investors to invest in firms with particular characteristics that suit their risk-return appetite. This effect applies to companies that emit signals, such as a liquidity premium, dividend policies, and tax rates, in line with the appetite of investors they seek to attract (Amihud and Mendelson, 1986; Miller and Modigliani, 1961; Pettit, 1977). Thus, the existence of heterogeneous preferences among investors may drive to a venture market segmentation, leading to the formation of preferential investment matching between certain types of investors and certain types of ventures.

Barberis and Shleifer (2003) support the idea that clientele aim to hold securities with a common predefined characteristic. These asset categories are named 'styles', and the process of allocating funds among styles rather than individual securities is termed 'style investing', which serves to simplify choice-related problems (Brown and Goetzmann, 1997; Mullainathan, 2000). An example of style investing is growth vs. value styles, respectively indicating a preference for assets with a high price-earning ratio vs. low price-earning ratio and attractive dividend yield. Blackburn et al. (2009) identify risk preferences as a potentially important attribute for distinguishing style investing preferences, while other works demonstrate that sentiment may be a determinant of clientele (e.g., Barberis et al., 2005; Kumar and Lee, 2005; Lamont and Thaler, 2003).

The clientele effect has attracted great interest in behavioral finance research, and its presence has been documented in several markets, including the stock market, corporate and treasury bond market (Chen et al., 2020), and recently in an online peer-to-peer lending market (Chen et al., 2022). Equity CFP is an essential new setting for exploring its presence. Barberis and Shleifer (2003) pinpoint two primary reasons for the emergence of new style investing for clientele in a market: (i) financial innovation, and (ii) detection of superior performance in a group of securities with a common characteristic. Equity CFPs embrace both. First, these platforms are rapidly spreading with the vigorous development of fintech and the surging demand for direct investment in start-up shares, democratizing access to the alternative finance market (Butticè and Vismara, 2022; Cumming et al., 2021). Second, CFP literature evidences that the firms' sector is an important consideration for crowd investors (Jhoan and Zhang, 2022). For instance, the high-tech sector is the second most represented on Crowdcube (2023) and raised the second highest amount (over $1 million) on Kickstarter (2023) in 2022. High-tech is a popular investment style (Brookfield et al., 2015; Froot and Teo, 2008). Hence, high-tech sector should identify a style investing in CFPs.

We refer to companies' characteristics as signals that could enhance the emergence of clientele-style investing among heterogeneous groups in the crowd. These signals are potentially informative because they can reveal venture categories. CFP investors are also expected to select entrepreneurial projects according to their risk tolerance and expected return.

2.2. Hypotheses development

The literature highlights that since entrepreneurs emit signals affecting crowd investors' decision-making process, campaign funding success is significantly related to the diffusion of high-quality signals (Lukkarinen et al., 2016; Vismara, 2016, 2018). Prior studies of signaling theories in CFPs have mainly focused on the role of the sender and the type of signal emitted, assuming a relatively homogeneous audience (Edelman et al., 2021). However, literature on equity crowdfunding evidences that the crowd is not a homogenous group (e.g., Ferretti et al., 2021; Goethner et al., 2020; Johan and Zhang, 2021; Wallmeroth, 2019). Instead, it comprises unsophisticated — Family, Friends, and Fools (FFF) — and sophisticated investors, such as business angels and venture capitalists (Ferretti et al., 2021; Shafi, 2021). More specifically, the true crowd that drives most investment activities is mainly formed of unsophisticated investors who invest small amounts with low frequency and have limited experience in processing new ventures' signals (Ferretti et al., 2021). Therefore, not all crowd investors have the same expertise in distinguishing high-quality from low-quality signals. The same signal may generate different responses depending on the type of investor it reaches and on the style of investing they pursue.

The high-tech industry may be considered a categorization criterion for clientele investment styles (Froot and Teo, 2008). Technological companies constitute more uncertain targets than those operating in traditional sectors, as it is difficult to assess the market potential of their innovative products (Carpentier and Suret, 2015; NOE and Rebello, 1996). In addition, because of their relatively young age, these companies frequently face resource constraints, limiting their ability to fully implement their strategy; this increases the uncertainty over future outcomes (Gimenez-Fernandez et al., 2020). Literature shows how these barriers raise investors' hesitancy to invest in innovative ventures

(Chandy and Tellis, 1998; Seth et al., 2020; Tansuhaj et al., 1991). Even if high-tech ventures raise the highest funds on CFPs and the degree of perceived innovativeness is an attractive element for investors (Chan and Parhankangas, 2017; Le Pendeven and Schwienbacher, 2023), they have the lowest likelihood of getting funded across all categories on Kickstarter, with only a 20% likelihood of closing the campaign successfully (Kickstarter, 2023).

At the same time, equity CFP investors participate in crowdfunding campaigns with the intention of realizing a financial return (Cholakova and Claryss, 2015). Accordingly, high-tech companies report the highest expected return and form the largest proportion of unicorn companies (start-ups with a market evaluation of over $1 billion). Thus, they may attract higher investment from investors with a high-risk propensity, regardless of these investors' ability to understand the ventures' signals. In a CFP, mismatches between signal type and investors' expertise and risk-return appetite appear more likely to affect the allocation of investments when unsophisticated investors are involved and when high-tech innovative campaigns are targeted. Therefore, drawing on the above insights, the following hypotheses are proposed:

H1. In CFPs, investment matching can be observed for only certain investor–entrepreneur combinations in terms of the amount invested.

H1a. In CFPs, various types of investors exhibit different investment propensities when considering high-tech innovative entrepreneurial projects.

From a clientele perspective, Barberis and Shleifer (2003) show how a group of investors present in a market may focus on subsets of investment presenting common characteristics. In their theoretical model, these investor groups coordinate purchases and sales of style portfolios based on common signals. These decisions sustain excess co-movement among subsets of securities. Even if the crowd is neither organized nor institutionalized, the collective behavior of groups of investors sharing a common investment style may emerge in CFP. Crowd investors make investment decisions based on multiple sources of information available at different times and through different channels, media, and other networks linked to the CFP. For instance, relevant information is obtained from the campaign page, investors' comments, and company activities on social networks and forums. Thus, investment decisions might not be primarily influenced by campaign signals but also by soft cues (Bachrach et al. 2022). When investors actively engage in a network such as one for a CFP, they also influence one another's behaviors and decisions (Xiao, 2019). For instance, investors may directly exchange information peer-to-peer. Another possibility is that investors make decisions based on what others have done (rational herding) or simply mimicking others (irrational herding). Information cascades that lead to herding behavior are well documented in crowdfunding literature (Hornuf and Schwienbacher, 2018; Vismara, 2016; Zaggl and Block, 2019). At the same time, emotional contagion or biases affect how the crowd operates resulting in inconsistent clear patterns or decision criteria (Mollick and Nanda, 2014). Nevertheless, regardless of the underlying mechanisms, which our study cannot directly observe or discern between, the salient point is that information spreading, homophily, or psychological dynamics as well as other phenomena can trigger collective behaviors by specific investor groups targeting specific ventures. Since which combination of investors and types of companies facilitates the emergence of collective behaviors in CFPs has not yet been investigated, this is the focus of our analysis.

On the investor side, literature evidences that unsophisticated investors have little incentive to expend much time or mental energy on a CFP as they invest small amounts and expect small returns. They prefer to rely mainly on others' behavior, rather than their own information (Ferretti et al., 2021), making them likely candidates to engage in collective behaviors. On the campaign side, technological and innovative companies present very high potential returns but are challenging to evaluate. Consequently, they attract many investors searching for golden unicorns (Estrin et al., 2018). Stock market studies have proved that collective behavioral schemes emerge for technological companies, as the collective behavior seeks to mitigate the associated risk (Cakan and Balagyozyan, 2016; Dehghani and Sapian, 2014; Hirshleifer and Hong Teoh, 2003).

Based on previous insights, this study investigates if the involvement of unsophisticated investors in collective behaviors depends on the companies they are targeting. Information asymmetry is especially prominent for unsophisticated investors trying to target high-tech and innovative companies. This contention leads us to propose the following hypotheses:

H2. In CFPs, collective behaviors can be observed only for certain investor–entrepreneur combinations in terms of the amount invested.

H2a. In CFPs, investors engage in collective behaviors when targeting high-tech innovative entrepreneurial projects.

3. Data and method

3.1. The sample

We collected publicly available data from the Crowdcube website about 81 funded equity crowdfunding campaigns between 2011 and 2016. This observation period is chosen to understand which type of investors and companies populate the CFP at the beginning of its activity and contribute to creating the CFP network. The Crowdcube platform opened in 2011 in the UK and is now one of the world's largest equity crowdfunding platforms and one of the most studied in equity crowdfunding literature (Vismara, 2016, 2018). From the Company House website (the UK Register of companies), we collected publicly available data about shareholders' information[3] on the number, the value, and the types of shares subscribed by each investor are collected (i.e., share A with voting rights, share B without voting rights). The final data set includes 8599 investments made by 5995 unique personal investors in 81 campaigns (Table 1). The following section describes the two sets of variables, one for companies and one for investors, considered in the analyses.

3.1.1. Information on Crowdfunded Companies

Identifying companies' clusters is based on ventures' signals and characteristics. Table 2 presents the descriptive statistics. On average, the percentage of *equity offered* during the campaign — low values are considered positive signals in the literature since it is related to the firm's risk (Ahlers et al., 2015) — is 17.7% of the total. On average, the number of exit strategies planned in the campaign (variable exits) is 1.1. Investors consider a planned exit strategy or liquidity event as a signal of future return on their investments (Ahlers et al., 2015). The number of *documents* published during the campaign, the number of *document pages*, and the number of *updates* posted on the platform are considered proxies of information disclosure, which helps companies to signal their value to the market (Verrecchia, 1990). In our dataset, companies publish, on average, 1.7 documents with 8.2 pages and post an average of 2.7 updates. Due to their recent foundation, the youngest firms need

Table 1
Sample descriptive statistics.

Sample	Obs.
Number of Companies	81
Number of Investors	5995
Number of Investments	8599
Number of Investments Share A	1844
Total amount invested	£16,680,804

[3] All companies incorporated in the United Kingdom are required by law to periodically file their accounts to Companies House. Information on shareholders are available after each company's capital variation.

Table 2
Companies' continuous variables: descriptive statistics.

	Obs.	Mean	SD	Min.	Max
Equity Offered (%)	81	17.7	8.2	4.0	48.0
Exits	81	1.1	0.8	0.0	4.0
Documents	81	1.7	1.5	0.0	5.0
Documents Pages	81	8.2	13.7	0.0	79
Updates	81	2.7	0.7	0.0	3.0
Team size	81	3.2	3.2	0.0	12.0
LinkedIn connections	81	37.3	67.9	0.0	303.0
Twitter followers	81	18.8	14.8	0.0	38.0
Company Age (years)	81	2.2	2.3	0.0	11
Sector:					
- Digital Service	81	39.5	-	-	-
-Food	81	29.6	-	-	-
-Leisure	81	19.8	-	-	-
-IT	81	9.9	-	-	-
-Other	81	1.2	-	-	-
Innovative (dummy)	81	22.2	-	-	-
Previous investors	81	24.7	-	-	-
Target Amount (£)	81	185,033.0	271,360.4	10,000.0	1900,000

to mitigate uncertainty in the market with other kinds of signals. The *team size* considers the number of people, besides the leading entrepreneur, that belongs to the venture's executive group.[4] This variable correlates positively with the outside perception of management's ability to cope with market uncertainty (Piva and Rossi-Lamastra, 2018). The average team comprises 3.2 members in the considered sample, with a maximum of 12. Other signals that can constitute an intangible asset for young ventures (Vismara, 2016) are the number of *LinkedIn connections* and *Twitter followers*. These signals measure the potential company supporter base and professional links. Companies in the sample have 37 LinkedIn connections and 19 Twitter followers on average.

We collected other variables that influence the quality of the signals emitted and are related to the company's characteristics. The *company's age* at the campaign time, on average, companies in the sample are two years old. The company's SIC (Standard Industrial Classification) code refers to the *sector*. Projects are grouped into five sectors: digital services (39%), food (30%), leisure (20%), IT consumer products (10%), and others (1%). SIC codes are also a consolidated taxonomy that has been commonly adopted to identify the company's innovation level with respect to the technological and knowledge intensity of a firm's sector (e.g., Khile and Philipps, 2009; Roper et al., 2009). Following the EU classification,[5] *innovative* companies are those that operate in high-tech industries and knowledge-intensive services, and according to this definition, 18 out of 81 of companies in our database are innovative. The participation of qualified investors in the company is monitored before the campaign by including a dummy which equals one if a business angel or venture capital has invested in the company in the years preceding the campaign, zero otherwise. In the sample, 25% of the projects involved qualified investors before the crowdfunding campaign (*previous investors* dummy variable). Finally, the total amount required by the companies to realize their projects, described by the variable *target amount,* controls the project's size. In the sample, the average target amount is £185,033 per campaign, with a maximum of £1900,000.

3.1.2. Information on Crowdinvestors

Equity crowdfunding investors are mainly concerned with monetary returns rather than intangible returns. Thus, in line with Wallmeroth (2019) and Ferretti et al. (2021), investors are categorized based on their investment activity. In particular, for the cluster analysis, the following variables are considered: (i) the *average amount invested* by each investor during the campaign as a proxy of investors' wealth (Estrin et al., 2018; Wallmeroth, 2019); (ii) the number of investments done by the single investors in the period, which reflects investors' experience as well as the degree of portfolio diversification (Goethner et al., 2020); (iii) the *percentage of shares A* (i.e., shares with voting rights) over the number of investments done by the investor to capture the engagement in the company (Cumming et al., 2019). Table 3 shows that on average, investors have made 1.4 investments with a total invested amount of 2782 £, and in 21% of cases, a share A was acquired.

3.2. Methodology

A CFP is a two-sided online marketplace where a heterogenous set of investors may use a wide range of information to make investment decisions. In this sense, it contains the two key features of a complex system. First, complex system approach postulates that behavior in a system is attributed to large populations of units that even when acting independently, through interactions, can display elements of emerging collective behavior. Second, in a complex system, it is possible to observe actors' interactions and detect significant patterns in the formation of actors' groups (Newman, 2011). Such properties pose challenges to conceptualizing the CFP, including the dominant methodologies adopted to study investment matching. In particular, it would be statistically improper to investigate investment matching and collective behaviors in a CFP using standard techniques like linear regression models that assume the independence of observations (Wisniewski and Rawlings, 1990). Considering the CFP as a complex network requires more advanced techniques that account for the interdependence of investment choices. In this sense, leading candidates are complex network techniques, especially the configuration model by Molloy and Reed (1995), which makes it possible to generate networks that are random (in terms of connections) but maintain specific characteristics of the original network to be tested. This method generates artificial networks that can be used as terms of comparison to test whether or not what is observed in the original network is ascribable to randomness. Moreover, as we focus on the existence of collective behaviors, we implement a community detection analysis (also from the research field of complex networks, see Fortunato and Hric, 2016) to find groups of close investors — those investing in some same companies. Implementing these two complex network techniques to study CFPs is one of the main contributions of our work.

Based on the aforementioned `configuration model', we generate two sets of null systems, namely $\boldsymbol{G}^*$ and $\boldsymbol{G}^\dagger$. The networks belonging to the first one are simply based on random investments (but the same number of investments for any investor) and they are used to test for the existence of significant investment matching between companies' and investors' different types. Thus, in this analysis, the original CFP network is tested against a large set of random networks in which the only feature that is preserved (equal to the one of the original CFP), is the number of investments that any investor does. Since in $\boldsymbol{G}^*$ the individual investments are fixed with respect to their number, but random with respect to the choice of the projects, these null networks represent a good term of comparison to test significant investment matching. For

Table 3
Investors' variables: descriptive statistics.

	Obs.	Mean	SD	Min.	Max.
Average amount invested by investors (£)	5995	2782.4	7612.6	0.2	139,461.2
Investment per investor	5995	1.4	1.5	1.0	61.0
% of Share A acquired on total investment	5995	21.3	38.5	0.0	100.0

[4] The variable *Team size* does not consider the main entrepreneur but exclusively additional team members working at the campaign. Thus, its value can be smaller than 1

[5] See the classification here: https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm

what concerning the second set of null networks, i.e., $\boldsymbol{G}^{\dagger}$, the networks belonging to it are built based on a further specification of the conditions used to generate the networks of $\boldsymbol{G}^{*}$, in the sense that – on top of the aforementioned constraint – another one is added. Indeed, in the null networks of $\boldsymbol{G}^{\dagger}$, the investor maintains both (i) the same number of investments and (ii) the same number of investments by type of company. Since in this second type of null networks there is no randomness in terms of investment matching, we can use it to study collective behaviors for any combination of investor type and company type. Even though in any network of $\boldsymbol{G}^{\dagger}$ the type of the companies that are selected by any investor is no longer subject to randomness (as in the first set of null networks, i.e., $\boldsymbol{G}^{*}$), the identity of the companies in which the investor invests is still subject to randomness. Therefore, these null networks can be properly used as a term of comparison to study if the observed concentration of investments that some investors (of a specific type) did in the same companies (of a specific type) can be considered random or not.

Two aspects have to be highlighted. The first is that community detection is based on investment structure — who has invested in what, and how much — whereas the investigation of investors' types considers investment exclusively from an individual perspective (see Section 3.2.1) — the amount invested and number of investments per investor. As these analyses are based on different features of the investment, both can use the invested amount without concerns about the empirical strategy followed. The second is that we evaluated different measures for the existence and weights of ties and we decided to use the size of the investments, as the alternative would be either problematic or less informative. Indeed, simply using the number of investments would exclude relevant information about the investment's relative importance. Another alternative would be to weight nodes through the type of share acquired (A with voting rights) and B (without voting rights), but this variable is highly correlated with the amount invested. Share A is generally associated with a high amount, while B with a low amount. Indeed, in the considered CFP network, we can observe that the 1844 investments of type A have an average value of 5187 £, while the 6755 investments of type B have an average value of 1053 £. Thus, adopting the amount invested captures two crucial aspects: the strength of the connection between investors and entrepreneurs and the commitment that different investors have to the company.

Finally, to test the significance of investment matching, as well as the significance of collective behaviors, we use the Kolmogorov-Smirnov test (Chakravarti et al., 1967; Kolmogorov, 1933), a non-parametric goodness-of-fit test requiring no assumption about the distribution of values. The rest of this subsection details the complex network approach developed to analyze the CFP as a network.

The set of observed investments can be represented as a bipartite network (Asratian et al., 1998), where the two classes of nodes are companies and investors, with edges weighted by the investment's monetary value. A schematic representation of the network is depicted in Fig. 1. Formally; the CFP bipartite network can be described as $G = \{A, B, E\}$, where:

- $A = \{1,., j,., I\}$ is the set of companies, and i represents the i-th company, I is the total number of companies. Hence $|A| = I$,
- $B = \{1,. i,., J\}$ is the set of investors, and j represents the j-th investor, J is the total number of investors. Hence $|B| = J$,
- $E = \{\omega_{i,j}: G_{i,j} > 0\}$ is the set of weighted links between investors $i \in B$ and companies $j \in A$, with $\omega_{i,j}$ indicating the amount invested.
- Ω_G indicates the total amount of money invested in the CFP G.

3.2.1. Cluster analysis: investigating CFP companies' and investors' heterogeneous characteristics

To identify the types of companies and investors active on the CFP, two separate cluster analyses are implemented, one for the companies and one for the investors. Information about companies refers to both continuous and categorical variables (Table 4); the study implements a Factor Analysis of Mixed Data (FAMD) followed by hierarchical cluster analysis (Pagés and Husson, 2013). Continuous variables are scaled to unit variance before running the FAMD. Then, based on the Euclidean distances between the resulting companies' coordinates in the 6 most important PCA dimensions (overall accounting for 64.8% of the variance), the dendrogram is formed using the Ward method to merge clusters progressively. It is important to remark that a possible issue for cluster analysis is the correlation between the available variables. To avoid such a problem, and especially in the case of a large amount of information (i.e., several variables), the FAMD is convenient as it initially runs a PCA process to reduce the original variables to the most

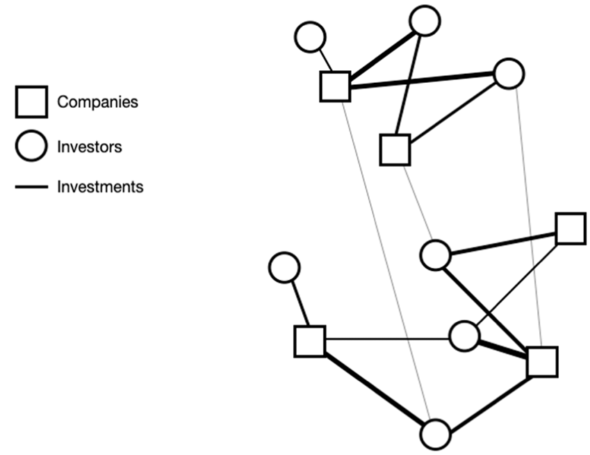

Fig. 1. : A schematization of the CFP bipartite weighted network, with connections' width representing the amount invested.

Table 4
P-values of T-tests on continuous variables considered for the cluster analysis of companies, by couples of clusters (*** = p-value $<$ 0.01; ** = 0.01 $<$ p-value $\leq$0.05; * = 0.05 $<$ p-value $\leq$0.1).

	I-II	I-III	I-IV	II-III	II-IV	III-IV
Target amount	0.004 ***	0.073 *	0.060 *	0.317	0.954	0.322
Equity offered	0.556	0.553	0.015 **	0.948	0.026 **	0.036 **
Exits	0.705	0.051 *	0.004 ***	0.004 ***	0.000 ***	0.177
Documents	0.002 ***	0.188	0.003 ***	0.199	0.000 ***	0.000 ***
Documents Pages	0.444	0.019 **	0.006 ***	0.038 **	0.000 ***	0.001 ***
Documents Updates	0.068 *	0.068 *	0.335	-	0.007 ***	0.007 ***
Age	0.007 ***	0.004 ***	0.345	0.091 *	0.198	0.021 **
Team size	0.001 ***	0.73	0.074 *	0.007 ***	0.000 ***	0.056 *
Linkedin connections	0.000 ***	0.523	0.014 **	0.002 ***	0.000 ***	0.041 **
Twitter followers	0.062 *	0.938	0.012 **	0.027 **	0.000 ***	0.002 ***

important and uncorrelated dimensions explaining their observed variations. [6]

For investors, the clustering process is performed with hierarchical agglomerative cluster analysis (Everitt et al., 2011) based on the three continuous variables described in Table 3. Also in this case, the dendrogram is formed using the Ward method to merge clusters progressively.

The length of the leaves of both resulting dendrograms (Fig. 2), suggests that the set of companies should be partitioned into four clusters (Fig. 2.a) and investors into three clusters (Fig. 2.b).

3.2.2. CFP investment matching based on clusters

To test HP 1, it is necessary to statistically compare the observed network of investments G with networks that emerge from random investments, namely random networks. This is necessary as, in the CFP, the independence of the observed investments cannot be assumed. Therefore, the methodology developed is based on the 'configuration model' (Cimini et al., 2019; Molloy and Reed, 1995; Newman, 2011), where an initial network is used as a reference and compared with multiple networks having the same density (i.e., the same number of edges as in the original network) and the same degree sequence (i.e., each node maintains the same number of connections as in the original network). Given the kind of system considered in this work, the study develops an original ad-hoc solution, whose details and implications are discussed below.

The model starts by computing the sum of the invested amounts of money, for each combination of (i) a cluster of investors k^B_β and a (ii) cluster of companies k^A_α. The statistic on which is based the analysis, namely η, is computed in percentage terms with regard to Ω_G, i.e., the overall amount invested on the CFP. Formally,

$$\eta(G,\alpha,\beta) = \frac{\Sigma\omega_{G,i,j}}{\Omega_G} * 100 \forall i \in k^A_\alpha, j \in k^B_\beta$$

A distribution of values to compare our observations needs to be considered to assess whether the values of η could be ascribed to randomness. Therefore, many networks are generated, G^*, where investments are established randomly. As in the original 'configuration model' (Molloy and Reed, 1995), the nodes' degree sequence (observed in G) is preserved in any random network, meaning that any node always maintains the same number of connections as in the original network. Then, the randomization of connections' weights is treated (i.e., the amount of each investment) as follows: the set of amounts invested by any investor is randomly associated with the set of investments in which the same investor is involved. Therefore, while the model preserves the investors' propensity to invest both in terms of the individual number of investments and personal amount invested, it only controls companies' ability to attract a certain number of investments (but not necessarily the same amount of money that they finally collect). This is set to test this system versus random networks in which investors' activities are always the same, while companies' signals may produce different levels of received investments.

This creates a set of 1000 G^* null networks, namely $\boldsymbol{G^*}$, and for each G^*, the computation of $\eta(G^*, \alpha, \beta)\ \forall\ \alpha, \beta$. Then, the Kolmogorov-Smirnov (KS) two-sided goodness-of-fit (GoF) test (Kolmogorov, 1933) is implemented to determine whether each $\eta(G, \alpha, \beta)$ can be ascribed to randomness, based on the percentile in which the latter falls with respect of the distribution of $\eta(\boldsymbol{G^*}, \alpha, \beta)$. The statistic on which the test is based, namely D, and the corresponding p-values, are reported in Table 5 of Section 4. Finally, to assess if the value of $\eta(G, \alpha, \beta)$ is higher ('+') or lower ('-') than expected, the analysis compares it with the median of the distribution derived from the null networks of $\boldsymbol{G^*}$. The results are discussed in Section 4.2.

3.2.3. CFP collective behaviors based on clusters

To explore whether investors display collective behaviors converging significantly amount towards the same companies (HP2), a community detection analysis in G is performed. The `community detection' analysis finds groups of `close investors' in the sense that they invest in some same companies. Once these groups are revealed, we test if the level of investments they exert in the common companies can be the result of a multitude of random individual processes, or not. As actors are heterogeneous, we check the presence of collective behavior not in generic terms, but for all possible combinations of one type of investor and one type of company. In this second part of the work, the null hypothesis considered as a reference for the analysis is that investors do have different preferences for the different types of companies, but also that investors are completely indifferent to the identity of the specific companies (among those of the considered type) in which they invest. In technical terms, it is possible to identify subsets of companies and investors that are 'structurally close', e.g., community, as represented in Fig. 3.b. [7] The study implements a widely used community detection algorithm, Infomap (Rosvall and Bergstrom, 2008). The algorithm divides the weighted network of investments in non-overlapping communities (Kheirkhahzadeh et al., 2016) composed of both investors and companies. Then, the performed community detection allows classifying all the observed connections in, on the one hand, *within-community* investments and, on the other hand, *between-communities* investments. The former investments are defined because the involved company and the involved investor belong to the same community. In contrast, for the latter ones, the two involved nodes belong to distinct communities (Fig. 3.c).

Similarly, to the process discussed above for η, we compute η^W, which considers the proportion of investment involving specific pairs of clusters (at a time) and exclusively occurring within the same community (*within-community* investments). Formally,

$$\eta^W(G,\alpha,\beta) = \frac{\Sigma\omega_{G,i,j}}{\Omega^W_G} * 100 \forall i \in k^A_\alpha, C_\gamma \wedge j \in k^B_\beta, C_\gamma$$

where Ω^W_G indicates the money that has been overall invested *within communities*, i.e., the sum of all the investments of G for which the involved investor and involved company belong to the same community γ. Like statistic η, also statistic η^W is expressed in percentage terms, but this time with respect to the overall amount invested *within-community*, i.e., Ω^W_G. While in principle it is possible to explore also the *between-community* investments, in the considered CFP the 98% of the money is invested *within-community*. Thus, the analysis is focused on this category of investment. It is important to remark that *within-community* investments are those that investors do on the same targets (i.e., companies) that are also selected by the group of investors with which the largest part of investments is in common.

Finally, to evaluate if investors only behave according to some individual preferences, or if there is some collective behavior for which

[6] In a cluster analysis, endogeneity is not usually considered nor tested, in the sense that cluster analysis is a statistical technique that makes it possible to group observations based on their observed characteristics, and therefore no cause-effect matter is discussed/considered/investigated. A possible issue for cluster analysis is the correlation between the considered variables. To avoid such issues in the presence of a large amount of information (i.e., several variables), we implement a Factor Analysis of Mixed Data (FAMD) followed by hierarchical cluster analysis. This methodology includes a PCA: "*Principal components analysis is a method for transforming the variables in a multivariate data set into new variables which are uncorrelated with each other and which account for decreasing proportions of the total variance of the original variables.*" (p. 29. Everitt et al., 2011).

[7] In case of companies to be 'structurally close' means to receive investments from some same investors, and in case of investors to be 'structurally close' means to invest in some same companies.

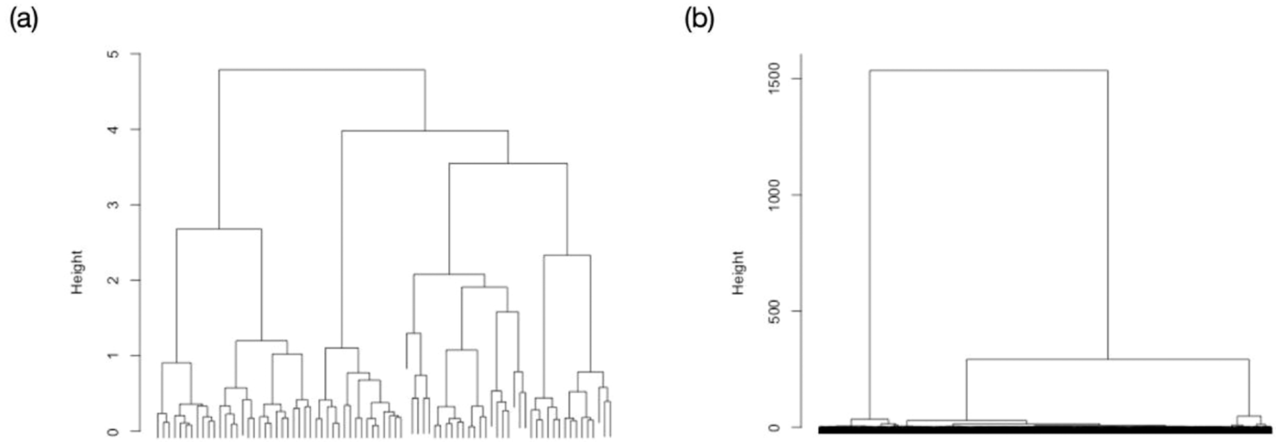

Fig. 2. : In (a) dendrogram resulting from the hierarchical clustering based on the 6 dimensions considered in the FAMD analysis of companies. In (b), dendrogram resulting from the hierarchical clustering based on the 3 variables considered for investors.

Table 5
Clusters of companies: labels, average values of the variables considered for the cluster analysis and number of companies, by cluster.

Clusters of Companies	K_1^A	K_2^A	K_3^A	K_4^A
Labels	**Innovative start-ups**	**Social-connected**	**Well-established**	**Lone Start-ups**
Team size (average)	2.4	5.3	2.7	0.9
Company Linkedin conn. (average)	13.9	84	20.6	0.6
Company Twitter followers (average)	18.3	27.3	18.7	17.6
Equity Offered (%, average)	15.2	16.5	16.7	23.4
Target Amount (£, average)	87,911.30	172,392.80	278,500.00	169,687.50
Exits (average)	1.4	1.5	0.9	0.6
Documents (average)	1.3	2.5	2	0.1
Update (average)	2.5	3	3	2.2
Document pages (average)	5.3	7	17.6	0.1
Company age (year, average)	1.1	2.1	3.5	1.5
Innovative (d)	10	3	5	0
Previous investors (d)	1	12	5	2
Sector by category:				
– Digital Services	7	17	3	5
– Food	-	11	2	11
– Leisure	-	-	16	-
– IT	8	-	-	-
– Other	-	-	1	-
Companies in the Cluster	15	28	22	16
(% over the total number of companies)	19%	34%	27%	20%

investors significantly opt for the same companies, it is necessary to build a new set of random networks, namely $G^{\dagger}$. To do so, another original ad-hoc variation of the 'configuration model' (Molloy and Reed, 1995) is developed, this time based on the network's subgraphs that are defined by the different clusters' combinations. This allows testing the observed CFP against random networks in which an investor's propensity to invest by type of company is always as in the observed network, and in which any company's signals always attract the same number of investments by type of investors, but the final amounts of money that is received may vary.[8]

In any $G^{\dagger}$ network, community detection is run (as in G) to identify *within-community* investments and compute all the possible $\eta^W(G^{\dagger}, \alpha, \beta)$ $\forall\, \alpha, \beta$. 1000 $G^{\dagger}$ are built and after computing $\eta^W(G^{\dagger}, \alpha, \beta)$ for any of them (based on the specific combination of α, β), the distribution of values is calculated. This is used as a term of comparison to test the value of the corresponding $\eta^W(G, \alpha, \beta)$ by means of the KS-GoF test previously introduced.

In addition, it is necessary to consider the diversification level of the investors involved in collective behaviors. For each combination of clusters (k_α^A, k_β^B), two sub-types of investors are distinguished. The first ones are those that invest exclusively in companies of the same network community and all of the same cluster (k_α^A). These investors who show a mono-dimensional approach are defined as 'parochial', and indicated with the symbol $\odot$. The second type is made of those investors that invest also beyond the boundaries of their community, and/or even beyond the boundaries of k_α^A. These investors, showing an approach in favor of diversification (in terms of network communities and/or cluster of companies), are defined as 'scattered', and indicate with the symbol $\otimes$. The $\eta^W(G, \alpha, \beta^{\odot})$ and $\eta^W(G, \alpha, \beta^{\otimes})$ are computed by considering the *within-community* investments performed by the investors $\beta^{\odot}$ and by the investors $\beta^{\otimes}$, at a time. Again, the statistical significance is tested through the KS-GoF test based on the empirical distribution determined by what is observed in $G^{\dagger}$ null systems. The results of this analysis are also discussed in Section 4.3.

4. Results

4.1. Categorization of companies and investors

The Clusters of Companies. The analysis yields 4 clusters (Table 5). The first cluster comprises 15 young companies that operate in the digital and IT sector (19% of the set). 10 out of 15 (67%) are identified as innovative businesses. Compared to other clusters, these firms disclose relatively fewer and shorter documents and have fewer LinkedIn Connections, likely due to their short lives. These companies requested less capital than the other clusters, on average £87,911 with 15% equity offered. This cluster is labeled high-tech *innovative start-ups*.

The second cluster consists of 28 companies (34% of the total) characterized by relatively large management teams (on average, 5.3 members) and a large base of social media connections. Compared with

[8] [] Further methodological details are available upon request to the authors

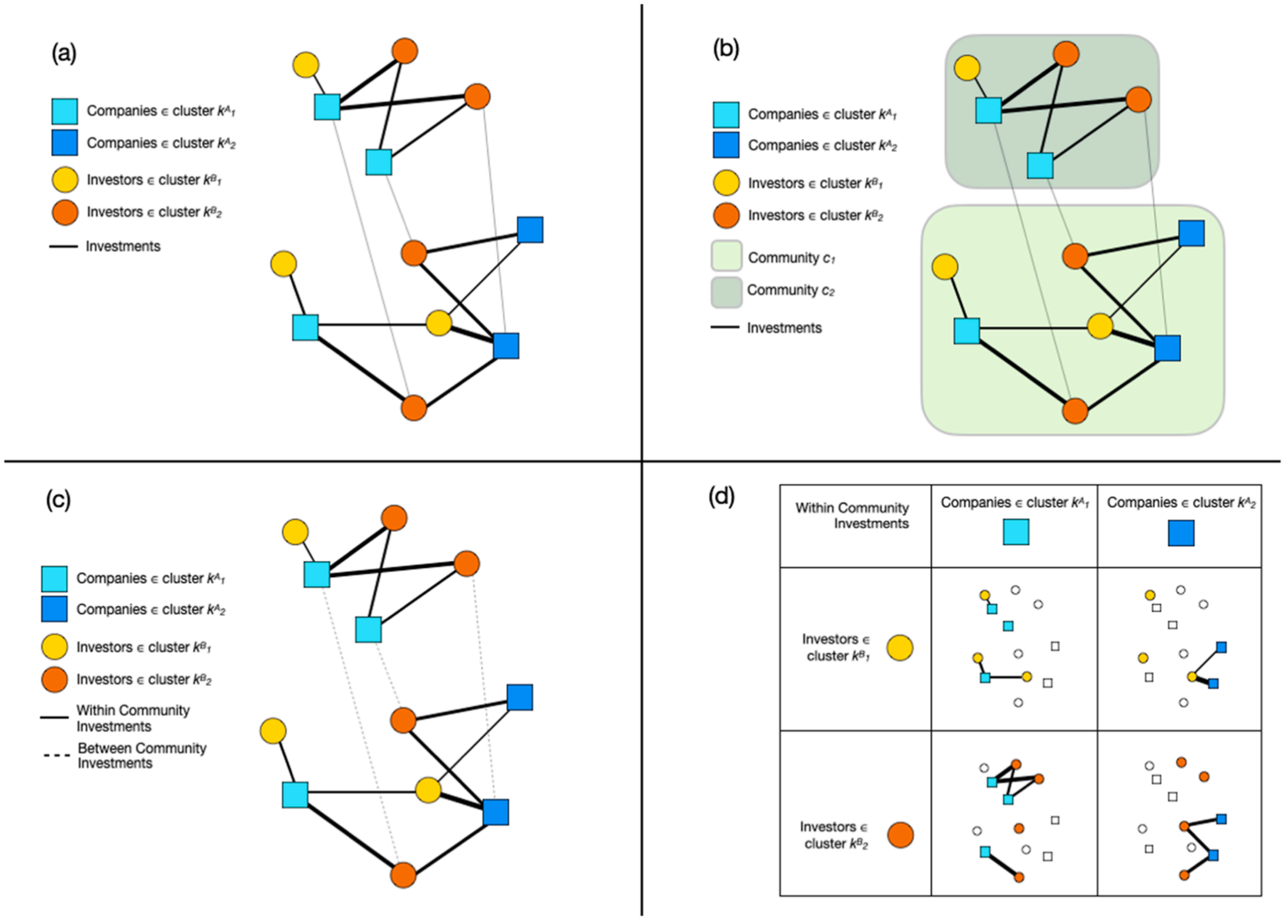

Fig. 3. : Schematic representation of the methodological approach for the analysis of collective behaviors. In (a), to account for heterogeneity of actors, types of companies (blueish colors) and types of investors (orangish colors) are revealed by means of two separate cluster analyses. In (b), the implementation of a community detection analysis reveals subsets made of 'structurally close' investors (greenish areas), i.e., investors that have invested in some same companies, and of the companies that the corresponding investors have mainly targeted. In (c), the detected network communities allow distinguishing *within-community* investments from *between-community* investments. Information on the identity of specific communities detected, i.e., light green community and dark green community, is no longer relevant, and *within-community* investments are exclusively considered. In (d), collective behaviors are investigated considering *within-community* investments by combination of companies' and investors' type. Then (not represented), what observed in the original network is tested versus what observed in a large number of null networks $G^{\dagger}$, in any of which the steps (b, c, d) are implemented.

other clusters, these companies publish more documents, on average 2.5. Companies in this cluster operate in the food and digital sector. Only 10% of them are innovative businesses, and 43% have institutional investors supporting the business before the campaign. Given their large social connections and high disclosure level, this cluster is named *social-connected companies*.

The third cluster includes 22 companies (27% of the total), characterized by their relatively longer lives (on average, 3.5 years) and by the most extensive funding requests in our dataset (on average, £278,500). The most salient characteristic of this cluster is that most of these companies (73%) have business projects related to leisure and consumer products. Therefore, this cluster is labeled *well-established company*.

The last cluster, including 16 companies (20% of the total), is composed mainly of start-ups. The entrepreneur is leading the campaign almost alone, as the average number of team members is small (on average, 0.9). These companies tend to provide less documental information, have fewer social media followers, and propose food sector projects with no innovative aspects. Consequently, these companies are labeled as *lone start-ups*.

The Clusters of Investors. Three clusters of investors are identified (Table 6). The first cluster, comprising the majority of the investors (73% of the total), is composed of people with low involvement in the company (low amount invested, on average £1284.4) and investing almost only in non-voting shares, resulting in infrequent investment activity (on average, 1.2 investments done). In line with the literature (Ahlers et al., 2015) this group is labeled as small investors. They are unsophisticated investors due to their relatively casual engagement in the crowdfunding campaign and their interest in supplying relatively small tranches of capital to a few projects. This cluster also comprises family and friends groups.

Contrastingly, the second cluster comprises a small number of investors (9% of the total) characterized by non-occasional investments (on average more than 4) of reduced amounts (on average £1362) focusing on shares giving voting rights. This cluster is labeled *serial investors*, defined in the literature as informal investors who have made more than three investments in privately-owned firms (Kelly and Hay, 1996). Such investors make many investments aware that few might generate returns and the rest are likely to fail (Estrin et al., 2018).

Finally, the last cluster is characterized by investors (18% of the total) investing relatively large sums (on average £7375), acquiring exclusively voting shares, and concentrating their investments in very few companies (on average, 1.0). Similar to Hornuf and Schwienbacher (2018), we consider that the investors putting large sums on the platform are likely to have a professional nature. In addition, the 100% of shares with voting rights requested by the investors of this cluster suggests the intention to be involved in the company's management or to take part in its governance (Cumming et al., 2019). Therefore, this cluster is labeled *high-value investors*.

4.2. Investment matching

Using the clusters as a starting point, the network of investments is leveraged to investigate whether investment matching emerges in the CFP (H1) and if high-tech innovative companies attract different investment propensities from specific groups of investors compared with other project categories (H1a). To do so, we consider the amounts of money invested by cluster combinations, i.e., the investments made by investors belonging to a specific investor cluster (k^B_β) in a specific company cluster (k^A_α). The results of this analysis are reported in Table 7.

In terms of sheer amounts, the largest sums are invested by *high-value investors* in *socially connected companies* (20% of total investments on the CFP) and *well-established companies* (16.8%), and by *small investors* in *socially connected companies* (14.5%) and *well-established companies* (13.9%). We next consider these amounts in relation to those observed in the null model. First, *small investors* make fewer investments than expected in *innovative start-ups* ($\eta = 1.8\%$, $p = 0.002$) but make more investments than expected in *well-established companies* ($\eta = 13.9\%$, $p < 0.001$). Second, *serial investors* make more investments than expected in *innovative start-ups* ($\eta = 2.9\%$, $p = 0.004$), as do *high-value investors* in *well-established companies* ($\eta = 16.8\%$, $p = 0.026$). Finally, *high-value investors* make fewer investments than expected in *lone start-ups* ($\eta = 7.1\%$, $p = 0.058$), though this result has weak significance. All other cluster combinations show investments in line with what would be expected from an investment network with the same distribution of investment sizes but random tie formation. Thus, investment matching emerges only for certain investor–entrepreneur combinations.

An important observation is that high-tech *innovative start-ups* tend to attract *serial investors* but not *small investors,* supporting H1a. *Small investors* tend not to seek extraordinary returns from their modest contributions (Chan and Parhankangas, 2017), whereas *serial investors* possess high expertise in evaluating signals from innovative and high-tech new ventures (Dimov and Murray, 2008; Kortum and Lerner, 2000). These considerations also help explain why *small investors* invest more than expected in *well-established companies*: the latter operate in familiar sectors such as leisure and propose easier-to-understand incremental changes (instead of potentially disruptive innovation). *Small investors* are also likely to be comforted by the high level of information in the market, making these ventures seem less risky.

The findings also show that *high-value investors* invest more than expected in mature companies presenting high information disclosure (i.e., *well-established companies*) and less than expected in companies with low information disclosure (e.g., *lone start-ups*). These results are in line with the insights of Auerswald and Branscomb (2003), who show that such investors are likely to be professionals and tend to avoid risky high-tech entrepreneurial firms, preferring developed business ideas more likely to become profitable in a shorter time.

Table 7
Clusters of investors: labels, average values of the variables considered for the cluster analysis, and number of investors, by cluster.

Clusters of Investors	k^β_1	k^β_2	k^β_3
Labels	**Small Investors**	**Serials Investors**	**High-value Investors**
Average amount invested by investors (£, average)	1284.40	1362.60	7375.40
Investment per investor (average)	1.2	4.1	1
% of Share A acquired on total investment (average)	0	40	100
Investors in the Cluster	4396	534	1065
(% over the total number of investors)	73%	9%	18%

4.3. Collective behaviors

The tests developed to examine H2 and H2a rely on the statistic η^W, which assesses the percentage of money invested *within-community* by cluster combinations. The observed values of these statistics and the corresponding p-values and signs (indicating if observed values are larger or smaller than expected) are reported in Table 8.

Results show that *small investors* are the only investor type for which collective behaviors are detected. It is possible to observe significant collective behaviors for two specific groups of companies: high-tech innovative start-ups and socially connected companies. When targeting high-tech innovative start-ups, small investors move in groups (i.e., in communities), resulting in larger than expected amounts of money invested. This pattern represents an 'incremental' collective behavior. Conversely, when targeting socially connected companies, small investors invest smaller amounts than expected, denoting a 'reductive' collective behavior.

To more deeply investigate this behavior, the analysis separates the investments of 'parochial' investors, who focus their activity exclusively *within-community* and exclusively in a specific type of company, from those of 'scattered' investors, who also invest *between-communities* and/or do not always target the same cluster of companies.[9] The results are strikingly different for the two cluster combinations. Considering the investments of *small investors* in *within-community innovative start-ups*, findings show that 'incremental' collective behavior is deployed exclusively by 'scattered' investors ($\eta^W(G, \alpha = 1, \beta = 1^{\otimes}) = 0.46\% > \eta^W(\boldsymbol{G}^{\dagger}, \alpha = 1, \beta = 1^{\otimes})$, $p = 0.008$). Conversely, considering the investments of *small investors* in *within-community socially connected companies*, findings show that 'reductive' collective behavior is deployed solely by 'parochial' investors ($\eta^W(G, \alpha = 2, \beta = 1^{\odot}) = 12.96\% < \eta^W(\boldsymbol{G}^{\dagger}, \alpha = 2, \beta = 1^{\odot})$, $p = 0.016$). All other types of investors, as well as *small investors* not targeting *innovative start-ups* or *socially connected companies*, either do not engage in spreading information or disregard it. In other words, when no collective behavior is detected, investors are moving

Table 8
Results of statistical tests concerning the invested amounts companies of cluster receive from cluster of investors. The values of the statistic $\eta(G, \alpha, \beta)$ report the percentage amount of money observed to be invested by the combination of clusters in the CFP. The last three columns report the values of the statistics D (on which the tests are based), the p-values and whether the observed values of η are smaller ('-') or larger ('+') than expected.

k^B_β	k^A_α	$\eta(G, \alpha, \beta)$	G^* D	p-value	+/-
Innovative start-ups	Small Investors	1.80%	0.999	0.002 ***	-
Innovative start-ups	Serials Investors	2.90%	0.998	0.004 ***	+
Innovative start-ups	High-value Investors	5.20%	0.799	0.402	
Social-connected	Small Investors	14.50%	0.849	0.302	
Social-connected	Serials Investors	5.20%	0.928	0.144	
Social-connected	High-value Investors	20.00%	0.549	0.902	
Well-established	Small Investors	13.90%	1	0.000 ***	+
Well-established	Serials Investors	4.00%	0.577	0.846	
Well-established	High-value Investors	16.80%	0.987	0.026 **	+
Lone Start-ups	Small Investors	6.40%	0.904	0.192	
Lone Start-ups	Serials Investors	2.30%	0.883	0.234	
Lone Start-ups	High-value Investors	7.10%	0.971	0.058 *	-

[9] See Section 3.2.3 for details. 'Parochial' investors are indicated by the symbols ⊙, while 'scattered' investors are indicated by the symbol ⊗.

independently of others' choices.

Overall, these results contribute to advancing the analysis of collective behaviors in the context of CFPs. Findings show that only *small investors* engage in collective behaviors and only for specific company types. When targeting *innovative start-ups*, small investors plausibly seek to compensate for their lack of financial skills and expertise by trusting some information they obtain. This leads them to act as groups, culminating in larger than-expected amounts being invested in commonly targeted companies. While the platform from which data are obtained does not provide a channel for direct communications among investors, peer-to-peer information exchanges among *small investors* may occur (e.g., via forums or social networks). Moreover, some sources of information may be followed by multiple investors (thus providing the same information to a multitude), and investors may observe and imitate one another.

The same motivations are likely relevant to the collective behaviors of some *small investors* when targeting *socially connected companies*. Interestingly, collective behavior results in lower than expected amounts being invested in common targets. In this sense, the behavior is still collective yet also reductive (in contrast to that observed for *small investors* targeting *innovative start-ups*). This action is plausibly in response to information that commonly attracts many small investors' attention. Indeed, *socially connected companies* are very active on social networks and, therefore, more able than others to reach potential supporters by spreading information (Fietkiewicz et al., 2018). The high connectivity that these companies can deploy, by means of intense LinkedIn and Twitter activity, allows them to catch the attention of investors with less skill and expertise, thus enabling the emergence of collective behaviors. In addition, the *small investors* involved in collective behaviors toward *socially connected companies* resemble supporter-like investors motivated by 'community' criteria, rather than mere profit (Vismara, 2019), or entrepreneurs' family members and friends.

5. Discussion and implications

This work identifies groups of investors and projects in equity crowdfunding,investigates the presence of preferential investment matching between company and investor clusters (H1, H1a), and the

Table 9

Results of statistical tests concerning the total amount of money the companies of a specific clusterhave received from the investors belonging to a specific cluster and that are located within the same community. The values of the η^W (*G, α, β*) statistics report the percentage amount of money observed to be invested *within-community* by a combination of clusters in the CFP. The table reports the values of the statistics *D* (on which the tests are based), p-values, and whether the observed values of η are smaller ('-') or larger ('+') than expected.

k_α^A	k_β^B	η^W (G, α, β)	D	$G^\dagger$ p-value	+/-
Innovative start-ups	Small Investors	1.80%	0.995	0.010 **	+
Innovative start-ups	Serials Investors	2.80%	0.673	0.654	
Innovative start-ups	High-value Investors	5.30%	0.666	0.668	
Social-connected	Small Investors	14.40%	0.995	0.010 **	-
Social-connected	Serials Investors	4.60%	0.669	0.663	
Social-connected	High-value Investors	20.30%	0.668	0.664	
Well-established	Small Investors	14.00%	0.678	0.645	
Well-established	Serials Investors	3.80%	0.684	0.632	
Well-established	High-value Investors	17.10%	0.668	0.664	
Lone Start-ups	Small Investors	6.50%	0.665	0.67	
Lone Start-ups	Serials Investors	2.20%	0.68	0.64	
Lone Start-ups	High-value Investors	7.20%	0.668	0.664	

emergence of collective behaviors in favor of specific types of companies (H2, H2a). Our study reinforces the literature on investment preferences and non-homogeneous behavioral profiles among crowd investors (Estrin et al., 2018; Ferretti et al., 2021; Goethner et al., 2020; Wallmeroth, 2019), as well as the literature discussing entrepreneurs' adoption of different signals (Ahlers et al., 2015; Lukkarinen et al., 2016; Vismara, 2016) as the base of clientele investment style in CFPs. Most importantly, we advance the field by simultaneously considering the characteristics of senders (i.e., entrepreneurs) and receivers (i.e., investors) to analyze clientele investment style in CFPs. The complex system approach reveals that the allocation of money in a CFP cannot be explained exclusively by either the sender's signals or the receiver's ability to understand them: we prove that it depends on the combination of the two. We also identify some types of investors with a significant propensity to invest (higher or lower than expected) only in some specific types of companies. Thus, our simultaneous consideration of heterogeneity on both sides of a CFP reveals that the presence of clientele investment style depends on the matches happening in the platform, and not exclusively on the characteristics of a single actor. This confirms H1.

Concerning innovative start-up financing, many studies have shown a negative relationship between investor preferences and a project's degree of innovation (e.g., Chan and Parhankangas, 2017). However, this relationship has not been thoroughly investigated, with crowd investors generally considered to be homogenous. Our results demonstrate that only small investors invest significantly less than would be expected in the most technological and innovative companies, confirming H1a, whereas serial investors significantly support this company type. We find that the relationship between innovativeness and the investment amount depends on the investor profile. By considering the various types of investor preferences, distinct types of entrepreneurs — especially those in innovative start-ups — can craft more meaningful and attractive signals for specific investors.

This work's second main contribution is its investigation of the emergence of collective behaviors in CFPs (Hornuf and Schwienbacher, 2018; Thies et al., 2018; Vismara, 2016; Zaggl and Block, 2019). The analysis reveals that collective behaviors occur exclusively among less sophisticated investors, i.e., small investors, also when targeting high-tech innovative start-ups, so confirming H2 and H2a only for this type of agent. It is important to recall that collective behaviors do not necessarily result from intentional coordination. Even if not directly communicating among themselves in a peer-to-peer manner, investors can draw on information from the same sources or observe other investors active on the CFP, leading to similar interpretations of signals and characteristics. This would imply the existence of a herding-like phenomenon. Also, it is important to remark that – due to data limitations – our investigation does not investigate the process leading to the observed collective behaviors. Thus, we need to remain agnostic on the nature of the processes generating them. Indeed, we test collective behaviors in the form of multiple emerging groups among investors of the same type. Thus, we demonstrate that collective behavior is one of the contributing mechanisms that drives the clientele effect. When groups of investors show collective behavior, they constitute another `clientele' from which entrepreneurial projects may take advantage. Future research should deepen understanding of the mechanisms enabling the formation of collective behaviors in CFPs, especially regarding the role of information spreading, homophily, or psychological dynamic.

From a practical standpoint, the observed positive collective behaviors of small investors toward innovative start-ups open new fundraising opportunities for these companies. Innovative start-ups could strategically influence small investors' propensity to finance them by simplifying and enhancing communication toward and among investors of this type and devising specific, ad-hoc signals. For example, previous studies reveal that using tools such as blogs, updates, and comments can reduce information asymmetry between entrepreneurs and investors, thus facilitating campaign success (Block et al., 2018; Clauss et al., 2018; Kang and Kim, 2020). Moreover, Wu et al. (2015) find that the frequency of announcements made by project founders is a predictor of funding success in the high-tech industry. We surmise that spaces of interaction among investors can not only influence campaign success in general but also specifically ease the exchange of information involving small investors, thus promoting the formation of groups focused on innovative investment targets.

Moreover, identifying which company and investor features characterize investment patterns in CFPs is relevant for both CFP managers and entrepreneurs seeking funds via these platforms. Indeed, as Kang and Kim (2020) point out, the survival and evolution of CFPs depend on satisfying individual participants' objectives and economic interests. Our results suggest that the evolutionary direction of CFPs also depends on how signal spreads, since this conditions how funds are allocated and thus, ultimately, investors' and companies' satisfaction. From this perspective, entrepreneurs trying to finance their ventures through CFPs should consider the existence of the clientele effect both in terms of investment matching and collective behaviors, and thus design funding campaigns aimed at stimulating and facilitating information spreading.

This study's analyses could be extended in several directions. First, our research focuses on the early dynamics of an equity crowdfunding platform. Further research should address the time dynamics and the evolution of a CFP network beyond initial growth. Second, our study is based on publicly available information for investor and project characteristics. More granular data or internal information sourced directly from a platform could improve the identification of investor clusters or more deeply uncover the dynamics of investment, such as whether changing a specific campaign feature could impact the amount invested. Third, our analyses take a systemic point of view, focused on identifying investors and venture categories using clusters. Therefore, we assess agents' activities at the group level, but not from an individual perspective. To test the extent to which our results can be extended to other setups, future research should consider other equity CFPs and different types of CFPs.

CRediT authorship contribution statement

Riccardo Righi: Formal analysis, Software, Writing – review & editing. **Simone Righi:** Methodology, Writing – review & editing. **Alessia Pedrazzoli:** Conceptualization, Writing – original draft, Writing – review & editing, Data curation. **Valeria Venturelli:** Supervision, Writing – review & editing, Data curation.

Declaration of Competing Interest

None

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