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Risk-taking behavior in financing new ventures through equity crowdfunding: an experimental and econometric analysis.

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L'assunzione del rischio nel finanziamento delle imprese tramite equity crowdfunding: un'analisi sperimentale ed econometrica.

Supervisor:
Prof. Caterina Lucarelli

Ph.D. candidate:
Francesco James Mazzocchini

Department of Management
Financial Markets and Institutions (SECS-P/11)

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To my family.
To my desire and eagerness for knowledge.
To my beloved German shepherd, Alaska, who passed away prematurely.

The loyalty and love of a dog to its owner is something unique and beyond thought.
Thank you, Alaska, for having made my life special every day.
Thank you, Alaska, for having made me a better human day by day.

First and foremost, I would like to express my sincere gratitude and admiration to my supervisor, Professor Caterina Lucarelli, for her patient guidance, enthusiastic encouragement and inspiring motivation in this enlightening journey.

Contents

List of Tables

List of Figures

Summary

Equity crowdfunding (hereafter ECF) is a recent phenomenon that leads entrepreneurial finance to take advantage of innovative digital facilities allowing ventures to obtain alternative financing: nascent entrepreneurs can raise capital from a crowd of investors, who generally contribute with modest individual amounts, during a web-based campaign for a certain period. ECF represents an innovative form of seed financing for new ventures. Following a pecking order approach, entrepreneurs might opt for this alternative financing scheme in the case that internal funds, external debt or external equity might not be sufficient or available.

ECF belongs to the Fintech environment and thus to the digital finance theoretical framework. It exploits availability of digital platforms able to support entrepreneurs in overcoming financial constraints, particularly relevant in the initial steps of ventures.

Investors in ECF must take decisions in a highly risky environment, with high levels of uncertainty. Moreover, potential profits (if any) would be appreciable only in a longer term and are subject to both liquidity and market risks. Therefore, the evaluation of the risk-return profile of an investment project is based on a multitude of determinants and encompasses a wide spectrum of disciplines.

All this explains why recent crowdfunding literature has followed rapid growth, and many authors have studied ECF from various perspectives and disciplines, following complementary points of view to understand what convinces the public to invest, determining the success, or failure of a fundraising campaign.

The thesis focuses on the equity crowdfunding from the perspectives of both entrepreneurs and investors. The theoretical background is built upon a multidisciplinary integrative framework that above all intersects: (i) entrepreneurial finance, (ii) pecking order theory, (iii) digital finance, (iv) social finance, (v) asymmetric information, (vi) contract theory, (vii) principal-agent theory, (viii) signaling theory, (ix) observational learning, (x) herd behaviour, (xi) information cascade, (xii) behavioural economics, (xiii) psychology, (xiv) corporate finance, (xv) traditional finance, (xvi) marketing, (xvii) computer science.

The aim of this research project is to analyse the dynamics of funding campaigns of new ventures on ECF platforms and identify the determinants of success. Assuming that investors refine their decision-making through observational learning of various signals,

the empirical settings hypothesize that an information cascade from different sources impacts on the outcome of the campaign by inducing *herding*.

The thesis is structured as a collection of papers and is articulated in three studies:

(1) *Success or failure in equity crowdfunding? A systematic literature review and research perspectives;*

(2) *Tapping the crowd for equity and herd behavior: a discrete choice experiment to elicit willingness-to-invest;*

(3) *From intention to action in financing new ventures: data mining and econometric analysis on real data.*

The first study consists of a systematic and bibliometric review of the literature on the determinants of the success or failure of an equity crowdfunding campaign, with particular leverage on the *signaling* technique as a tool to alleviate information asymmetries by entrepreneurs/management and is aimed at identifying the research gaps where to position the two subsequent studies.

The second study follows the perspective of investors (objective: investor willingness-to-invest) and is part of the literature of *information cascade and herding*. It observes investment decisions in the context of equity crowdfunding through a choice experiment with the aim to empirically verify the hierarchy of sources that affect the willingness to invest. In fact, it is assumed that retail investors perfect their decision-making framework through the observation of information cascades deriving from more informed/experienced parties.

The third study examine the perspective of entrepreneurs (objective: determinants of a successful ECF campaign). The aim is to identify on real-world data the signals that effectively affect the decision-making of investors and generate herding, among those conveyed via information cascades. In other words, the aim is to capture the effect of signaling mechanism on the outcome of an ECF campaign. Following the *Theory of Planned Behavior*, in fact, the objective of this third work is to move from investment intentions (study 2; analyzed experimentally) to the concrete behavior of investors (observed in real data), by looking at the outcome of real-world ECF campaigns.

Abstract (Italiano)

L'equity crowdfunding (da qui ECF) è un fenomeno recente che porta la finanza imprenditoriale a sfruttare le innovative strutture digitali che consentono alle imprese di ottenere finanziamenti alternativi: gli imprenditori nascenti possono raccogliere capitali da una folla di investitori, che generalmente contribuiscono con modesti importi individuali, durante una campagna online per un certo periodo. L'ECF rappresenta una forma innovativa di finanziamento sia per le startup ai primi stadi di sviluppo che per le imprese. Seguendo un approccio di ordine gerarchico, gli imprenditori potrebbero optare per questo schema di finanziamento alternativo nel caso in cui i fondi interni, il debito da terzi o il capitale esterno potrebbero non essere sufficienti o disponibili.

L'ECF appartiene all'ambiente Fintech e quindi al quadro teorico della finanza digitale. Sfrutta la disponibilità di piattaforme digitali in grado di supportare gli imprenditori nel superamento dei vincoli finanziari, particolarmente rilevanti nelle fasi iniziali delle iniziative.

Gli investitori in ECF devono prendere decisioni in un ambiente altamente rischioso, con alti livelli di incertezza. Inoltre, i potenziali profitti (se presenti) sarebbero apprezzabili solo a lungo termine e sono soggetti sia a rischi di liquidità che di mercato. Pertanto, la valutazione del profilo di rischio-rendimento di un progetto di investimento si basa su una moltitudine di fattori e comprende un ampio spettro di discipline. Tutto questo spiega perché la recente letteratura sul crowdfunding abbia seguito una rapida crescita, e perché molti autori abbiano studiato l'ECF da varie prospettive e discipline, seguendo punti di vista complementari per capire cosa convince il pubblico a investire, determinando il successo o il fallimento di una campagna di raccolta fondi.

La tesi si concentra sull'equity crowdfunding dal punto di vista sia degli imprenditori che degli investitori. Il background teorico è costruito su un quadro integrativo multidisciplinare che ricomprende, principalmente: (i) finanza imprenditoriale, (ii) teoria dell'ordine gerarchico, (iii) finanza digitale, (iv) finanza sociale, (v) informazione asimmetrica, (vi) teoria dei contratti, (vii) teoria principale-agente, (viii) teoria della segnalazione, (ix) apprendimento osservazionale, (x) comportamento della mandria, (xi) cascata di informazioni, (xii) economia comportamentale, (xiii) psicologia, (xiv) finanza aziendale, (xv) finanza tradizionale, (xvi) marketing, (xvii) informatica.

Lo scopo di questa ricerca è quello di analizzare le dinamiche delle campagne di finanzi-

amento su piattaforme di ECF e identificare le determinanti del successo. Supponendo che gli investitori perfezionino il loro processo decisionale attraverso l'apprendimento derivante dall'osservazione di vari segnali, le impostazioni empiriche ipotizzano che una cascata di informazioni provenienti da fonti diverse abbia un impatto sull'esito della campagna inducendo comportamenti imitativi.

La tesi è strutturata come una raccolta di articoli ed è organizzata in tre studi:

(1) *Success or failure in equity crowdfunding? A systematic literature review and research perspectives;*

(2) *Tapping the crowd for equity and herd behavior: a discrete choice experiment to elicit willingness-to-invest;*

(3) *From intention to action in financing new ventures: data mining and econometric analysis on real data.*

Il primo studio consiste in una revisione sistematica e bibliometrica della letteratura sulle determinanti del successo o del fallimento di una campagna di raccolta di equity crowdfunding, con particolare leva sulla tecnica del signalling come strumento per alleviare le asimmetrie informative da parte degli imprenditori/management, ed è volto ad individuare i gap di ricerca ove inserire i due studi successivi.

Il secondo lavoro si pone nella prospettiva degli investitori e si inserisce negli studi dell'effetto herding e delle cascate informative, osservando, grazie ad un esperimento di scelta, le decisioni d'investimento nel contesto dell'equity crowdfunding, e verificando empiricamente la gerarchia delle fonti che condizionano maggiormente la disponibilità ad investire (willingness-to-invest). Si assume infatti che gli investitori retail perfezionino il proprio quadro decisionale attraverso l'osservazione di cascate informative derivanti da soggetti più informati/esperti.

Il terzo studio mira ad esaminare, ponendosi ora nella prospettiva degli imprenditori e delle imprese, i fattori derivanti dalle cascate informative in grado di influenzare l'esito di una campagna di finanziamento. Applicando la Theory of Planned Behavior, infatti, l'obiettivo di questo terzo lavoro è di passare dalle intenzioni di investimento (studio 2), studiate sperimentalmente, al comportamento concreto degli investitori, osservando dati reali di campagne di raccolta effettivamente concluse.

Part I

Wisdom of the crowd or following the pack?

Chapter 1

Introduction

"A smooth sea never made a skilled sailor."
[Franklin D. Roosvelt]

1.1 Raising funds from the crowd

Crowdfunding is the process through which a certain amount of money is raised via an open call from a vast number of people, namely the crowd, which contributes generally with modest amounts.

Although it is commonly thought to be a very recent phenomenon, it draws its origins from the early XX century, when the basement of the Statue of Liberty was almost entirely funded by a crowd of citizens (Harris, 1985). In fact, Joseph Pulitzer, the owner of the prestigious journal "The World", in 1885 decided to launch a fundraising campaign to support the work on the pedestal. He raised 100,000$ from 120,000 donors through the pledge of printing their names on his journal. Most of the contributors donated less than a dollar. Some historians even argue that the concept of crowd raising was already present in the XVI century in a more rudimentary version (Bracco et al., 2011). According to them, the Dutch East India Company, a publicly trading company in Netherlands, had a capital of almost 6,500,000 guilders endorsed by 1,200 shareholders (Ames, 2008).

However, it is only recently when it has been considered an alternative and innovative financing method and subject to stricter regulations. In fact, thanks to the advent of the digital era, it has become a mainstream mean of funding in the arts, music and games communities (Agrawal et al., 2014).

In modern literature can be found four main types of crowdfunding models: donation-based, reward-based, debt-based and equity. The former consists in a philanthropic process where people contribute freely to certain charitable causes, without expecting any direct return for their effort. It is defined also as patronage model by Mollick (2014). However, the overwhelming majority of crowdfunding campaigns are based on returns that could be either financial or non-financial benefits.

The reward-based model is still probably the most widespread and is based on bids made with the expectation of a concrete return, that usually consists of a sample or pre-sell of the product that the issuer releases in order to reward the backers. The same product will eventually be placed on the market later on if the fundraising target is met and the business takes-off.

The debt-based approach is commonly known as lending or peer-to-peer model. It consists in a loan granted by the crowd in return for some interests on the amount lent other than the reimbursement.

The latter type is more sophisticated than the previous ones. The issuer is generally a startup or a firm that needs to meet the fundraising target for a specific purpose. The backers receive some shares of the firm's equity in return for their contributions and thus turn into investors. Belleflamme et al. (2014) define this model as "profit sharing crowdfunding", while the reward based as "pre-ordering crowdfunding". Hence, due to its degree of sophistication it is also subject to stricter regulations (Heminway and Hoffman, 2010).

Recently, two additional categories have also been identified: software-value token and litigation. The first one is commonly associated to Initial Coin Offerings and consists in raising seed finance through the release of tokens, which are generally a quantity of certain cryptocurrencies (O'Dair and Owen, 2019). The latter is a form of financing legal actions with peer's money in exchange for a stake in the plaintiff's claim, if the case succeeds or is settled, or a different kind of reward (Elliott, 2016).

As already stated, the focus of this thesis will be on the equity crowdfunding side.

1.2 Equity crowdfunding success

Success in equity crowdfunding can be analyzed from three different perspectives. The first one relates the pre-screening phase in which a campaign is presented to an equity crowdfunding platform for acceptance. The platform evaluates the project and decides whether to accept it for going live on their website to raise crowd-financing. The evaluation process consists in conducting due diligence check on the company and directors, analyzing the business idea, the team composition and a detailed business plan (Kleinert and Volkmann, 2019). Then before going live startups might have the chance to start off with a soft launch of a private-fundraising mode for a certain period of time, where founders' families, entrepreneurs, friends, or those belonging to the platform's lead investor network can have a prior access to the funding campaign. Then when 20% or 30% of preliminary investment is reached (e.g., FundedByMe), the campaign goes public. The basic idea is that a private round can boost the probability of closing the public round successfully by enhancing the crowd confidence through a head-start. However, founders might as well decide to start off directly with a public round if they feel confident that they will succeed. According to the British equity crowdfunding platform Crowdcube e.g., only 10% of the firms presented on the pre-screening phase successfully reach the second phase (Kleinert and Volkmann, 2019). At the public stage, startups can finally launch their live campaign and reach crowd-investors. The project will be live for a certain period, displayed on the headings of each campaign in order to show the investing time left. The crowd, i.e. registered members of the platform accredited as investors, can pick one or more projects and make an investment by buying one or more shares. The campaign closes when the time is up or as soon as it reaches the maximum goal. It is indeed crucial that the founders set effectively the two thresholds of the fundraising. Firstly, they have to set the minimum amount of financing that they would like to raise through the campaign, i.e. minimum funding goal or target, which will state the success of the campaign once reached, but does not prevent from receiving extra funding (i.e. overfunding) as long as the funding window is still open. Secondly, a maximum funding goal has to be set as well, in order to limit the amount of share offered to the crowd and keep it under control. Therefore, the second success perspective, which could be defined as in-campaign success, looks at the capital raised and in greater detail to the funding percentage. In particular, when the latter equals 100%, it means that the minimum target is reached, and the campaign is already successful. After that, the funding might still flow in as long as there is still some time left and the campaign goes into overfunding until the closing or until it reaches the maximum funding goal. This second success stage means that not only the platform has accepted, and thus trusted, the campaign but even the crowd had confidence in the project. However, this does not mean that an investment has been successful. In fact, from an investor's perspective it is riskier to fund a campaign that reaches the minimum goal rather than a campaign that does not reach it and thus does not get financed. In the latter case indeed, all the shares backed will be returned to the crowd, thus transferring away from it any risk. Here comes the third success perspective, which can be assessed only ex-post. An investment made on an equity crowdfunding platform is successful if and only if the investor is able to make a gain and thus obtain a return. It materializes if the startup is able to create value in the medium-long term, to wit enter and remain in the market, produce cash flows and grow towards a more mature stage. In other words, returns occur when after some years (i.e. the Italian law allows startups to release dividends only after four years from their company registration[1]) the company's board will decide to pay out dividends or when the investor is able to find a counterpart on the secondary market willing to buy the shares at a higher price. Thus, at this stage the ex-post success of an equity crowdfunding campaign is measured from the crowd point of view and is subject to dividend and liquidity risks.

Fig. 2.1 summarizes the three overmentioned success stages with a focus on equity crowdfunding campaigns.

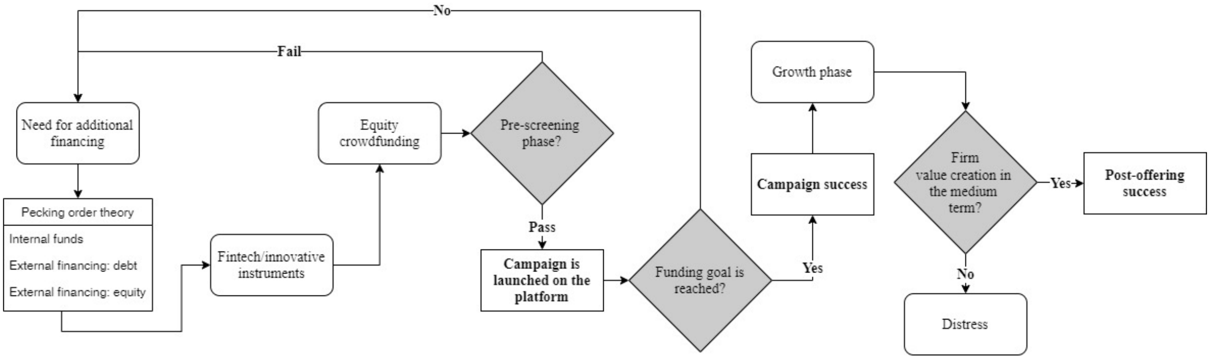

Figure 1.1: Success in equity crowdfunding.

1.3 Thesis purpose and research gap

The thesis focuses on the equity crowdfunding from the perspectives of both entrepreneurs and investors. The epistemological approach of thesis consists overall of an abductive reasoning, where a pragmatist perspective is adopted to merge the strengths from deductive and inductive reasonings and overcome their individual weaknesses (Josephson and Josephson, 1996). In particular, the research started from an exploratory observation of

[1]D.l. 179/2012

the phenomenon, adopting an abductive reasoning. However, the following studies are individually based on deductive approaches, but their linkages take on inductive reasoning.

The theoretical background is built upon a multidisciplinary integrative framework that above all intersects: (i) entrepreneurial finance, (ii) pecking order theory, (iii) digital finance, (iv) social finance, (v) asymmetric information, (vi) contract theory, (vii) principal-agent theory, (viii) signaling theory, (ix) observational learning, (x) herd behaviour, (xi) information cascade, (xii) behavioural economics, (xiii) psychology, (xiv) corporate finance, (xv) traditional finance, (xvi) marketing, (xvii) computer science.

The aim of this research project is to analyse the dynamics of funding campaigns of new ventures on ECF platforms and identify the determinants of success. Assuming that investors refine their decision-making through observational learning of various signals, the empirical settings hypothesize that an information cascade from different sources impacts on the outcome of the campaign by inducing herding.

The thesis is structured as a collection of papers and is articulated in three studies:

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The first study consists of a systematic and bibliometric review of the literature on the determinants of the success or failure of an equity crowdfunding campaign, with particular leverage on the signaling technique as a tool to alleviate information asymmetries by entrepreneurs/management and is aimed at identifying the research gaps where to position the two subsequent studies.

The second study follows the perspective of investors (objective: investor willingness-to-invest) and is part of the literature of information cascade and herding. It observes investment decisions in the context of equity crowdfunding through a choice experiment with the aim to empirically verify the hierarchy of sources that affect the willingness to invest. In fact, it is assumed that retail investors perfect their decision-making framework through the observation of information cascades deriving from more informed/experienced parties.

The third study examine the perspective of entrepreneurs (objective: determinants of a successful ECF campaign). The aim is to identify on real-world data the signals that effectively affect the decision-making of investors and generate herding, among those conveyed via information cascades. In other words, the aim is to capture the effect of signaling mechanism on the outcome of an ECF campaign. Following the Theory of Planned Behavior, in fact, the objective of this third work is to move from investment intentions (study 2; analyzed experimentally) to the concrete behavior of investors (observed in real data), by looking at the outcome of real-world ECF campaigns.

1.4 Background from literature reviews on crowdfunding

Recently, some scholars have conducted literature reviews of the crowdfunding phenomenon. Nevertheless, past reviews were conducted from a general perspective or focusing on different models than the equity-based crowdfunding (e.g. reward, donation). Alternatively, for those conducted on ECF, the article selection was not exhaustive (i.e. meagre sample size) and without biases (i.e. unclear inclusion/exclusion criteria), or the methodologies were not systematic and comprehensive, nor covered the full extant body of literature.

At the time of writing this thesis, no other systematic reviews have focused on both success and failure sides of equity-based crowdfunding campaigns and there are no articles in the existing literature that address this issue. Indeed, browsing[2] the Elsevier's search engine, Scopus, only one result arise: Mochkabadi and Volkmann (2020). However, this article differs from the aim of the first study of this thesis (i.e. Study one, chapter 2) in that its purpose is not focused on uncovering drivers of success (or failure) of campaigns, but rather offers a detailed overview of the ECF phenomenon and a description of its context.

Therefore, to the best of our knowledge, as literature lacks a comprehensive and multidisciplinary systematic analysis of drivers of success of ECF campaigns, the first study of this thesis means to fill this gap and contribute to the advancement of the

[2]Search string: ("equity" AND "crowdfunding" AND "systematic" AND "review").

field in several ways. Table 1.1 provides a synthesis of other previous review studies on crowdfunding (in general) success[3] with the aim to better position the thesis, and lay the ground for its first study (i.e. Study one, chapter 2). Eight reviews, including the one from Mochkabadi and Volkmann (2020), arise.

However, apart from the aforementioned study from Mochkabadi and Volkmann (2020) and the study from Shneor and Vik (2020), previous reviews contemplate other crowdfunding models than the equity based. The latter tries to suggest useful causal models according to each CF type, but is built on the analysis of a scarce number of research publications (e.g. for the ECF model 8 articles only are considered).

In a nutshell, compared to extant reviews, the first study of this thesis differs from several aspects. First, our systematic review focuses its attention on equity-based models of crowdfunding. Second, its focus of analysis is on the main drivers for conducting a successful campaign, such as characteristics of nascent entrepreneurs, businesses, and/or campaigns, able to convince the crowd to believe in ventures and undertake investment risks. An inevitable deduction is that lack of these drivers and/or presence of concurrent features may cause the failure of the campaign. Third, the analysis of findings follows a multi-disciplinary approach, based on the different concurring and complementing perspectives (managerial, financial, technological, psychological ones) necessary to understand the ECF.

1.5 Thesis implications and future lines of research

Theoretical implications

Implications for academics are advancements on knowledge of both causes of the success/failure of ECF campaigns and factors that drive investors' willingness-to-invest, within a wide spectrum of disciplines.

First, we offer a comprehensive understanding of key themes and dominant concepts involved in this issue and draw a possible agenda for scholars to undertake further theoretical exploration. Indeed, research should exploit more pioneering and unconventional theories, such as those related to behavioral/psychological approaches. As far as research methods are concerned, literature on ECF is lacking adoption of Big Data and AI tools, as those related to machine and deep-learning models, following both supervised and

[3] Search string: "systematic review" AND "crowdfunding" AND "success"

Reference	Research objectives	Scope	Sample
Mochkabadi and Volkmann, 2020	(1) How has ECF literature evolved since its establishment? (2) Which perspectives dominate research on ECF? (3) What are the emerging themes that dominate ECF research and what future research is needed?	Categorization of ECF into 5 different perspectives: Capital Market, Entrepreneur, Institutional, Investor, and Platform.	113 contributions (including non-peer-reviewed articles) from 2012 to 2017
Shneor and Vik, 2020	(1)What are the common trends and practices in early CF success research? (2) What are unaddressed gaps in early CF success research? (3) What are most prevalent factors affecting CF success across studies?	To present a set of suggested causal models for each CF type	88 academic papers from 2010 to 2017 (of which 8 on ECF)
Popescul et al., 2020	(1) What are the main characteristics for each type of crowdfunding campaign and the most important platforms used to attract investors? (2) Do the crowdfunding campaigns feature disruptive characteristics? (3) What are the investors' psychological motivations involved in crowdfunding campaigns? (4) What are the success factors of social media-based crowdfunding campaign for the start-up projects?	Identifying, analyzing, and classifying general and specific factors of investor psychological motivation in CF.	58 documents until 2019 (on all CF models)
Serwaah, 2021	(1) What specific conditions account for gender differences at each stage of the CF process? (2) How do researchers conceptualise gender within this field? (3) To what extent has this new form of fundraising achieved the promise of financial democracy by offering females an equitable alternative path in the entrepreneurship funding process?	Review the literature at the intersection of crowdfunding and gender, while examining the extent to which crowdfunding has enhanced female financial inclusion and participation	47 studies from 2011 to 2021 (of which 12 on ECF)
Böckel et al., 2021	To what extent do the research foci in the scientific literature on CF and sustainability contribute to unleashing the potential of CF to facilitate sustainable development?	To gain an overview of what CF types are most frequently researched and assess whether (and how) a sustainability orientation influences the success of CF campaigns	83 peer-reviewed papers on CF until 2018
Alegre and Moleskis, 2021	(1) What does the discipline know about the motivations and behavioral decision-making of the crowd in the absence of monetary benefits in CF, i.e., in the space of rewards and donations? (2) What factors determine that reward- and donation-based projects are successfully funded, and how? (3) What have we learned about the post-funding performance of such projects?	To presents an interdisciplinary systematic review of the literature on donation-based and reward-based CF	63 articles from 2009 to 2018 (of which 19 on donation CF and 44 on reward CF)
Alhammad et al., 2022	To review and identify factors impacting backers' behavior by conducting a SLR.	To comprehensively identify factors impacting backers' behavior toward using reward CF: Team Characteristics, Project Characteristics, Social Influence, User Generated Content, Risk, Distrust, Upfront Marketing, Environment Readiness, and Backers Motivation.	33 papers from 2012 to 2019
Hou et al., 2022	To comprehensively investigate which factors lead to the success of medical CF campaigns.	To identify categories of factors that affect the success of medical CF: platforms, raisers, donors, and campaigns.	13 articles from 2010 to 2020

Table 1.1: Previous review articles on success in crowdfunding

unsupervised learning approaches.

Second, the phenomenon involves different perspectives and at least three main avenues could be identified: entrepreneurs' perspective, investors' perspective and platforms' perspective. Further research interested in the first perspective, should start from the reasons for which entrepreneurs should be looking for ECF, proceeding with the changes in attitude towards risk of entrepreneurs, until focusing on post-offering experience of successfully financed ventures. As far as investors' perspective is concerned, literature should investigate drivers for investors' willingness-to-invest in ECF campaigns, their attitudes towards risk and risk-return preferences, also comparing different crowdfunding models. As for platforms, fewer authors have investigated business models of ECF platforms, starting from the pre-screening phase of campaigns and the evaluation criteria adopted, until the post-offering services provision to ventures.

Another promising avenue for research lies in cross-country-cross-platform analysis of the phenomenon to extend, both numerically and geographically, the sampling of observations of ECF campaigns, thus capturing cultural differences. Scholars have much room also for comparing theories and causal effects across different crowdfunding models.

A fourth layer of implications originate from the adoption of an experimental methodology (i.e. the Discrete Choice Experiment) to test hypotheses in line with behavioural economics. Indeed, experimental economics and behavioural economics have much in common, but also multiple differentiators (Loewenstein, 1999). The second study of this thesis paves the way for academic debate which shall move forward and try to combine methodological rigour to adherence to reality. The former often requires constraints of abstraction and simplifications in order to ensure the internal validity of the experiment and thus *"draw confident causal conclusions"*. The latter requires a relaxations of those constraints in order to achieve external validity and thus *"the possibility of generalizing the conclusions to situations that prompted the research"* (Loewenstein, 1999.

Fifth, as prospective investors appear to take use of herd behaviours to increment their information set, a main issue remains still wide open: "is herding a beneficial or detrimental behavior for investors willing to invest in ECF?". Although literature often addresses it with a negative acceptation (i.e., as a behavioral bias: herd bias or herd mentality bias), it might actually turn out to be a "rational" heuristic (Gigerenzer, 2018), because individuals easily maximize the personal available information set by following choices of more informed/skilled parties. Therefore, implications for further research can be disentangled according to two perspectives. On one hand, at the individual level, investors are able to easily maximise their information set, by attempting to reduce asymmetric information, and pick more promising projects. On the other hand, at the aggregate level, the effect represent a double-edged sword. Market benefits from more allocative efficiency deriving from reliable and genuine information disseminated through a cascade. However, the market may suffer from increasing systemic risk, as information manipulations (or simply judgement errors) at the top steps of the cascade inevitably and rapidly propagate among less informed and skilled investors.

A sixth layer of implications is connected to the latter and involves bad practices. Indeed, it is essential to control for moral hazard in signalling schemes, as a FinTech environment can catalyse information sharing and thus induce manipulations. For instance, entrepreneurs themselves or platform owners might manipulate information cascades by making a non-confirmed bid during the campaign and withdraw the investment before the conclusion in order to attract late investors (Meoli and Vismara, 2021).

Practical implications

We acknowledge that ECF is a valuable tool to support entrepreneurial finance and, as a result, ECF development could contribute to the spread of innovation and economic growth. This motivates the policy implications of this thesis, positioned within a large multidisciplinary framework, and different according to the actors involved.

First, entrepreneurs are proved to be experiencing changes of scenario and should adapt their behaviors to deal with the present digital era. Those willing to access to an alternative financing scheme, such as ECF, should be aware of the variety/complexity of skills requested to successfully manage digital campaigns as their attitude and communication skills can highly influence the outcome of their financing requests.

Second, platform managers could improve their knowledge of what persuades the crowd to invest, with more efficient project pre-screening. Additionally, considering the quicker and easier information sharing in FinTech environments, systemic risk might be catalysed. Hence, platforms, acting as financial intermediaries, are appointed not only to admit to official listing more promising projects but also to filter out untrustworthy information cascades and obstruct moral hazards. In this way, they are able to downsize cognitive limits and biases affecting investors, thus reducing systemic risk.

Third, to this end, supervisory authorities and regulators are not only required to ensure transparency and trustworthiness of information disseminated, but also to induce financial awareness among investors and encourage a better financial education.

Fourth, crowd-investors should be aware of bad practices and manipulation and possibly verify the reasonableness of information cascades, as well as try to rely on more trustworthy sources of information.

As a concluding remark, the Covid-19 pandemic seems to have fostered investments in ECF. This is probably due to the increment of digitalization and FinTech usage during lock-downs imposed by government authorities, as well as to the resilient adoption of more innovative and inclusive marketing and promoting means. It is likely that this trend is not going to stop in the near future and thus a massive usage of FinTech means, and in particular digital investments, is expected.

References for Chapter 1

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some simple economics of crowdfunding. *Innovation Policy and the Economy*, *14*(1), 63–97. https://EconPapers.repec.org/RePEc:ucp:ipolec:doi:10.1086/674021

Alegre, I., & Moleskis, M. (2021). Beyond financial motivations in crowdfunding: A systematic literature review of donations and rewards [cited By 6]. *Voluntas*, *32*(2), 276–287. https://doi.org/10.1007/s11266-019-00173-w

Alhammad, M., Tan, C., Alsarhani, N., & Zolkepli, I. (2022). What impacts backers' behavior to fund reward-based crowdfunding projects? a systematic review study [cited By 0]. *Pacific Asia Journal of the Association for Information Systems*, *14*(2), 90–110. https://doi.org/10.17705/1pais.14207

Ames, G. J. (2008). The globe encompassed : The age of european discovery, 1500-1700.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, *29*(5), 585–609. https://doi.org/http://dx.doi.org/10.1016/j.jbusvent.2013.07.003

Böckel, A., Hörisch, J., & Tenner, I. (2021). A systematic literature review of crowdfunding and sustainability: Highlighting what really matters [cited By 9]. *Management Review Quarterly*, *71*(2), 433–453. https://doi.org/10.1007/s11301-020-00189-3

Bracco, D. G., Massa, C., & Fontana, C. (2011). Dall'espansione allo sviluppo: Una storia economica d'europa. *Torino: Giappiachelli.*

Elliott, M. (2016). Trial by social media: The rise of litigation crowdfunding. *University of Cincinnati Law Review*, *84*, 8.

Gigerenzer, G. (2018). The heuristics revolution: Rethinking the role of uncertainty in finance. *The behavioural finance revolution.* Edward Elgar Publishing.

Harris, J. (1985). *A statue for america: The first 100 years of the statue of liberty.* Four Winds Press.

Heminway, J. M., & Hoffman, S. R. (2010). Proceed at your peril: Crowdfunding and the securities act of 1933. *Tenn. L. Rev.*, *78*, 879.

Hou, X., Wu, T., Chen, Z., & Zhou, L. (2022). Success factors of medical crowdfunding campaigns: Systematic review [cited By 0]. *Journal of Medical Internet Research*, *24*(3). https://doi.org/10.2196/30189

Josephson, J. R., & Josephson, S. G. (1996). *Abductive inference: Computation, philosophy, technology.* Cambridge University Press.

Kleinert, S., & Volkmann, C. (2019). Equity crowdfunding and the role of investor discussion boards. *Venture Capital*, *21*(4), 327–352.

Loewenstein, G. (1999). Experimental economics from the vantage-point of behavioural economics. *The Economic Journal*, *109*(453), F25–F34.

Meoli, M., & Vismara, S. (2021). Information manipulation in equity crowdfunding markets. *Journal of Corporate Finance*, *67*, 101866.

Mochkabadi, K., & Volkmann, C. K. (2020). Equity crowdfunding: A systematic review of the literature. *Small Business Economics*, *54*(1), 75–118.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of business venturing*, *29*(1), 1–16.

O'Dair, M., & Owen, R. (2019). Financing new creative enterprise through blockchain technology: Opportunities and policy implications. *Strategic Change*, *28*(1), 9–17.

Popescul, D., Radu, L., Păvăloaia, V., & Georgescu, M. (2020). Psychological determinants of investor motivation in social media-based crowdfunding projects: A systematic review [cited By 1]. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.588121

Serwaah, P. (2021). Crowdfunding, gender and the promise of financial democracy: A systematic review [cited By 0]. *International Journal of Gender and Entrepreneurship*. https://doi.org/10.1108/IJGE-07-2021-0115

Shneor, R., & Vik, A. (2020). Crowdfunding success: A systematic literature review 2010–2017 [cited By 15]. *Baltic Journal of Management*, *15*(2), 149–182. https://doi.org/10.1108/BJM-04-2019-0148

Part II

Study one

Chapter 2

Success or failure in equity crowdfunding? A systematic literature review and research perspectives

"Some fortunate people are more optimistic than the rest of us.
They are not average people.
They got to where they are by seeking challenges and taking risks."
[Daniel Kahneman]

Abstract

Purpose – This paper provides a multidisciplinary framework that allows an integrated understanding of reasons of success or failure in equity crowdfunding (ECF), a Fintech digital innovation of the traditional entrepreneurial finance. This comprehensive analysis identifies a future research agenda related to this alternative financing technique.

Design/methodology/approach – A systematic literature review (SLR) was chosen for the purpose as it consists of an explicit, pre-defined, transparent, structured and replicable stepwise process to ensure that the maximum number of relevant articles are methodologically appraised. The review was conducted on 127 documents extracted from two multi-disciplinary repositories: Elsevier's Scopus and Clarivate Analytics Web of Science. After a systematized series of inclusion and exclusion criteria, in line with our objectives and conceptual boundaries, a final list of 32 peer-reviewed articles written in English was analyzed by the authors through a meta-synthesis and thematic analysis to identify the key themes and dominant concepts.

Findings – Results show that the body of literature is recent and fast growing. The proposed integrative framework of existing research indicates that the outcome of an ECF campaign is related to signals conveyed by entrepreneurs in form of hard information (firm characteristics, financial information, business characteristics and project description) and soft information (intellectual capital, human capital, social capital and social media network), catalyzed by digital media that facilitate also personal interactions between entrepreneurs and investors. Similarly, external factors (investor and campaign characteristics, with the fundamental role of ECF platform managers in building trust between entrepreneurs and investors) allow for the alleviation of information asymmetries. The present study sheds lights on which signal mechanisms are decisive in improving the outcome, taking into consideration various disciplines which follow different but complementary perspectives.

Practical implications - Entrepreneurs should adapt to the transition towards the digital era, exploiting alternative financial instruments and learning effective signaling strategies, within a large variety of skills requested. Platform managers can obtain more focused information on selected entrepreneurial projects more efficiently.

Originality/value – Although it is fast-growing, the field of research is very recent and still fragmented and limited to the perspective/discipline followed. This SLR is, to the best of the authors' knowledge, the first multidisciplinary and integrative analysis of reasons that motivates success, or failure, of an ECF campaign. The digital nature of ECF encourages future research to move towards more pioneering and unconventional theories and research methods. Hence, we add to the existing literature by proposing future patterns of research, based on an integration of highly technological skills and behavioral/phycological approaches.

Keywords: *Equity crowdfunding, Success, Failure, Systematic literature review, Entrepreneurship, Pecking order theory, Fintech*

Paper type: *Literature review*

2.1 Introduction

Equity crowdfunding (hereafter ECF) is a recent phenomenon that leads entrepreneurial finance to take advantage of innovative digital facilities (Cumming, Deloof, et al., 2019) allowing ventures to obtain alternative financing: nascent entrepreneurs can raise capital from a crowd of investors, who generally contribute with modest individual amounts, during a web-based campaign for a certain period. ECF represents an innovative form of seed financing for new ventures, where entrepreneurs lacking personal funds, and following a pecking order approach (Myers and Majluf, 1984) might not yet be able, or willing, to access bank loans (Kirby and Worner, 2014) generally more expensive, or to engage in initial public offering (IPO) procedures.

ECF belongs to the Fintech environment (Blaseg et al., 2021) and exploits availability of digital platforms able to support entrepreneurs in overcoming financial constraints, particularly relevant in the initial steps of ventures (Eckhardt et al., 2006). In the past decade, this phenomenon has been acknowledged as an alternative financing technique and regulated by national authorities in many countries, among others the U.S.A. and western European countries. In its true meaning, equity crowdfunding is 'alternative' to other traditional financial patterns such as, venture capitalist, banks or other specialized entities (business angels, incubators, etc.). In fact, the goal of an equity crowdfunding campaign is to raise a predetermined amount of capital within a certain timeframe, meaning that the project needs to be able to attract and persuade an adequate number of crowd-investors, thus obtaining the targeted capital.

Indeed, the crowd of investors in ECF must take decisions in a highly risky environment, with high levels of uncertainty, and potential profits (if any) would be appreciable only in a longer term. Therefore, the signals sent by entrepreneurs to persuade the crowd return to bring into play the central issue of asymmetries of information between lenders and borrowers. The digitalization of the venue itself, such as web based ECF platforms, boosts opportunities of connections and sharing of information between entrepreneurs and investors, reducing the distance between the two categories and altering the traditional asymmetries in an unpredictable way. Concurring drivers emerge affecting these asymmetries (Troise et al., 2019): innovativeness of project (Schmitz et al., 2017), but also ability of self-marketing, or of personal branding (Sadiku-Dushi et al., 2019), entrepreneurs' personal characteristics and her/his behavior, reliability of founders and network ties (Shane and Cable, 2002), ability to receive trust, and so on.

All this explains why recent crowdfunding literature has followed rapid growth, and many authors have studied ECF from various perspectives and disciplines, following complementary points of view to understand what convinces the public to invest, determining the success, or failure of a fundraising campaign. Thus, research contributions on ECF range from studies on entrepreneurship to strategic management; from corporate finance to behavioral economics; from marketing to organization; from psychology to engineering and computer science. Therefore, in this article we ask, "How do the various disciplines that study ECF contribute and complement each other towards an integrated understanding of the success, or failure, of an ECF campaign?".

In fact, to the best of our knowledge, literature lacks a comprehensive and multidisciplinary analysis of causes of success, or failure of ECF campaigns. This paper means to fill this gap by uncovering drivers for conducting a successful campaign, such as characteristics of nascent entrepreneurs, businesses, and/or campaigns, able to convince the crowd to believe in ventures and take investment risks. An inevitable deduction is that lack of these drivers and/or presence of concurrent features may cause the failure of the campaign.

Given the research question of the paper, we have opted for a reasoned methodology, which could, on the one hand, gather studies from the widest range of disciplines available, but on the other hand, it relies on the strict selection procedure of research products to adequately limit the analysis. Therefore, a systematic review was conducted to cover the whole existing literature on ECF success and failure, exploiting two multidisciplinary repositories, such as Elsevier's Scopus and Clarivate Analytics Web of Science. Initially, for the period 2015-2022, 127 documents were extracted. Nevertheless, inclusion and exclusion criteria, applied in line with the process of Tranfield et al. (2003)(Petticrew and Roberts, 2008; Briner, Denyer, et al., 2012; Palmatier et al., 2018) generated a final sample of 32 articles, considered for detailed investigation.

Findings on main research approaches are qualitatively synthesized and show that research has moved along time from the analysis of traditional characteristics of new ventures and business sectors to more innovative characteristics related to the entrepreneur, the board of directors of the startup with their interconnections, to the campaign rounds, and internet-based aspects, such as the social media network, to the presence of pitch videos, or pictures, and the frequency of updates on the project. The entrepreneur's self-image, the kind of person she/he is and her/his behavior transmitted by the media, due to ECF positioning in the Fintech environment, becomes increasingly relevant in attracting financing, and determining the campaign success.

Implications for academics are advancements in knowledge of what causes the success/failure of an ECF campaign, within a large spectrum of disciplines, as we offer a comprehensive analysis of key themes and dominant concepts involved in this issue. Furthermore, we draw a possible agenda for further research, that definitively should exploit more pioneering and unconventional theories and research methods, such as those related to behavioral/phycological approaches as well as those related to Big Data and AI tools.

As far as practical implications are concerned, entrepreneurs who are willing to access an alternative financing technique, such as ECF, should be aware of the variety/complexity of skills requested to successfully manage the digital campaigns.

This work is organized as follows. The next section presents the theoretical background and sets the stage for the review. Then, the methodological procedure is thoroughly outlined. Next, the main findings and research agenda are discussed before drawing the conclusions.

2.2 Background from the literature

2.2.1 Entrepreneurial finance, pecking order theory and signals

Since the seminal papers of Donaldson (2000) and Myers and Majluf (1984), finance theory suggests that entrepreneurs requiring funds to undertake their ventures follow a pecking order and prioritize their sources of finance in order to reduce their costs: they organize their capital structure according to the financing costs, which depend on the information asymmetries between firm management and new shareholders (Myers and Majluf, 1984). Accordingly, the pecking order theory indicates that, firstly, firms opt for internal funds which are immune from information asymmetry; if internal funds are not available, firms issue debt in the form of bank debt or bond issue. If internal funds and bank/bond financing are limited, then the equity issue is considered. So, the latter is regarded as a lender of last resort and less preferable due to higher information asymmetries, dilution of ownership and thus higher costs of financing.

Financing initial ventures is an outstanding issue (Eckhardt et al., 2006;Shane and

Cable, 2002; Cumming, Deloof, et al., 2019) as entrepreneurs do not have sufficient personal funds, they not only face constraints of bank loans (credit rationing), but also lack requirements to access Stock Exchanges, either for bond or stock issues (Kirby and Worner, 2014). This scarcity of funds, together with the high level of information asymmetries of early stages, motivates the grounds for the development of ECF, which is a valid alternative for new ventures looking for subordinate means of financing (Walthoff-Borm, Schwienbacher, et al., 2018), even if it could be interpreted also as a last resort option: in fact, it could happen that unprofitable firms, excessively indebted or firms with more intangible assets or lacking internal funds, could be more prone to look for ECF (Walthoff-Borm, Schwienbacher, et al., 2018). Equity funding is placed lower in the pecking order scale because it is more sensitive to information asymmetry than external debt, and thus more costly to compensate investors for adverse selection risk, which is high especially during the initial stages of ventures (Sapienza and Gupta, 1994; Sorenson and Stuart, 2001). Thus, ECF can downscale information asymmetry by easing access to information of new ventures and allowing entrepreneurs to signal their true quality, thanks to the use of new technologies and the Fintech environment (Blaseg et al., 2021).We mainly assert that ECF investments might be interpreted as a principal-agent issue (Jensen and Meckling, 1976), where the agent (the nascent entrepreneur) is better informed about the outlook of the investments and the principals (investors) suffer from asymmetric information. Therefore, new venture founders should signal their true quality by conveying as much information as possible to attract crowd-investors.

Coherently, applying the signaling theory (Spence, 1973; Connelly et al., 2011), investors interpret signals sent from entrepreneurs to the market and try to evaluate the fundamental value of new ventures, resulting in an alleviation of adverse selection caused by asymmetric information. Consequently, the entrepreneurs' ability to signal and persuade the crowd of investors will result in a successful campaign and thus in the attainment of entrepreneurial finance in the form of ECF; otherwise, the outcome will be negative and result in a failure of the campaign.

2.2.2 The ECF process and campaign outcome

A new venture in need for new financing might opt for traditional or innovative methods, in accordance with the pecking order theory (Myers and Majluf, 1984). In the case it chooses the ECF scheme (Figure 2.1), it must first overcome a pre-screening phase before launching the campaign, where the project is presented to an ECF platform for admission (Zhang et al., 2019). In this phase, managers of the ECF platform analyze the business idea, the business plan and the entrepreneurial team, conducting a due diligence check and deciding whether to accept it (Kleinert and Volkmann, 2019a). Only 10% of the projects successfully reach the public phase (Kleinert and Volkmann, 2019a). Before going live, entrepreneurs could choose to start off with a soft launch in a private-fundraising style, where founders' families and friends, or the platform's network can have prior access to the funding so that a private head-start can boost the likelihood of being funded (Lukkarinen et al., 2016).

Once the campaign is open for funding, if it reaches at least its minimum goal, the new venture receives the raised financing resources.

A smaller number of papers consider the post-funding dimension and possibly the value creation of the venture in a longer term (Walthoff-Borm, Vanacker, et al., 2018).

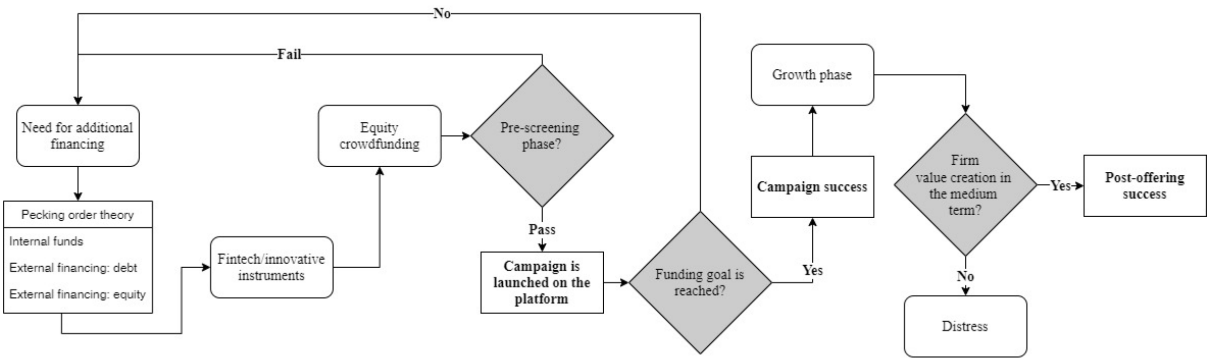


Figure 2.1: Stepwise representation of the ECF process

2.3 Methodology: the search protocol of SLR

2.3.1 Choosing a review methodology

As shown in recent studies, a systematic literature review (SLR) is to be preferred to other non-structured review methodologies whenever the researcher aims to provide a critical state-of-the-art understanding of the extant literature on a specific research topic (Tranfield et al., 2003; Petticrew and Roberts, 2008; Briner, Denyer, et al., 2012; Palmatier et al., 2018; Pascucci et al., 2018; Battisti et al., 2021). Compared to other non-systematic review types (e.g. narrative reviews), a SLR consists of an explicit, pre-defined, transparent, structured and replicable stepwise process to ensure that the maximum number of relevant articles are methodologically appraised (Tranfield et al., 2003; Petticrew and Roberts, 2008; Pascucci et al., 2018; Leonidou et al., 2020; Battisti et al., 2021; Vrontis et al., 2022). A systematic approach overcomes some of the limitations of narrative reviews and minimizes the researcher bias (Briner and Walshe, 2014; Pascucci et al., 2018; Battisti et al., 2021; Vrontis et al., 2022). It provides more reliable and generalizable findings from which comprehensive conclusions can be drawn, giving a high-quality scientific significance (Briner, Denyer, et al., 2012; Palmatier et al., 2018; Leonidou et al., 2020).

Therefore, we adopted a SLR procedure following the stepwise process outlined by Tranfield et al. (2003) and practices provided by recent review studies in management (e.g., Pascucci et al., 2018; Pret and Cogan, 2018; Leonidou et al., 2020; Battisti et al., 2021): (i) formulation of the research question; (ii) definition of the review protocol; (iii) descriptive analysis of the results; (iv) meta-synthesis and thematic analysis of the data.

2.3.2 Research question and definition of the review protocols

This paper focuses on outcomes of ECF and contributes to extant research by understanding the set of signals, emerging in various fields and disciplines, that may contribute to alleviate information asymmetries between entrepreneurs and investors, within a Fintech environment. Hence, we developed the following research question: *"How do the various disciplines that study ECF contribute and complement each other towards an integrated understanding of the success, or failure, of an ECF campaign?"*. Thus, our research objectives (Pret and Cogan, 2019) are:

(i) To synthetize an unambiguous definition of ECF, as an alternative financing scheme, and of its process;

(ii) To evaluate different disciplines and related perspectives, either qualitative or quantitative, adopted to analyze ECF outcomes, and synthetize them in an integrative framework;

(iii) To identify determinants of successful/unsuccessful outcome in an ECF campaign that grant/prevent access to finance;

(iv) To draw insight from the literature in order to advance future research on determinants of ECF outcomes and signaling strategies;

(v) To infer a research agenda from existent literature with insight on topics worthy of investigation.

Given the various disciplines involved, as indicated in the research question of this paper, firstly, we need to select multidisciplinary internet-based repositories, and opt for two search engines instead of just one, to make the search more comprehensive and enhance the review to the utmost (Pascucci et al., 2018; Vrontis et al., 2022): Elsevier's Scopus and Clarivate Analytics Web of Science (WoS). Moreover, we decided to base our research on Scopus and WoS, as they include multidisciplinary studies and their search functions allow for sufficient accuracy, as well as being frequently browsed together in SLR studies to achieve a broader coverage of the extant literature (Waltman, 2016; Pascucci et al., 2018). Then, we set the conceptual boundaries (Pret and Cogan, 2018; Battisti et al., 2021) in terms of elicitation of the two dimensions of ECF outcome, with regard to success or failure.

Steps performed to identify the final sample of articles were systematized into a series of inclusion and exclusion criteria (Tab. 2.1), in line with our objectives and conceptual boundaries (Pascucci et al., 2018; Pret and Cogan, 2018; Leonidou et al., 2020; Battisti et al., 2021).

We applied two extraction queries based on a general keyword search requirement with open search timespan, to make sure that all relevant articles were included (Leonidou et al., 2020). However, we included only documents written in English (Pascucci et al., 2018; Leonidou et al., 2020; Battisti et al., 2021; Vrontis et al., 2022).

The first query was based on the concurrence of three keywords, "equity", "crowdfunding" and "success", browsed among the title, abstract and keywords sections of documents (Leonidou et al., 2020; Battisti et al., 2021). It produced 138 documents, of which 23 overlapping, resulting in a sub-sample of 88 documents.

Similarly, the second query browsed for "equity", "crowdfunding" and "failure" or "unsuccessful" to uncover the complementary side of an ECF outcome and were added to the first, where the word "success" possibly also covered for the adjective "unsuccessful", but not for the noun "failure". For the two queries, we opted for the co-occurrence of

Inclusion criteria and queries (Q1, Q2)	Ex-ante exclusion criteria	Ex-post exclusion criteria
(i) Documents available in at least one of the two databases: Elsevier's Scopus and Clarivate Analytics Web of Science; (ii) Q1: Documents that contain (not necessarily in this order) "Equity", "crowdfunding" and "success" within title, abstract or keywords; Q2: Documents that contain (not necessarily in this order) "Equity", "crowdfunding" and "failure" within title, abstract or keywords; (iii) No timespan boundaries (all published documents); (iv) Documents available in English.	(i) Non-peer-reviewed documents: - Book chapters; - Reports; - Lecture notes; - Conference proceedings; - Others. (ii) Duplicates.	(i) Articles that examine different types of crowdfunding rather than ECF; (ii) Articles that do not examine success/failure factors of campaigns; (iii) Articles focused on post-funding dimension; (iv) Articles focused on pre-funding dimension; (v) Articles that examine other non-pertaining or non-focused topics; (vi) Non-empirical articles

Table 2.1: Inclusion and exclusion criteria

general keywords combining standard Boolean operators[1] ("AND", "OR"; Pascucci et al., 2018; Pret and Cogan, 2018; Leonidou et al., 2020; Battisti et al., 2021; Vrontis et al., 2022). The keyword definition is guided by our research question to center the ECF phenomenon and its outcome (Pret and Cogan, 2018; Battisti et al., 2021). At the same time, the use of broad keywords prevented relevant articles from being filtered out from the initial sample (Pret and Cogan, 2018; Leonidou et al., 2020).

The second query produced 35 documents, of which 14 duplicates and 26 overlapping the first query, resulting in a sub-sample of 13 documents and in an initial sample of 127 documents from the two queries.

In line with similar studies, the ex-ante exclusion criteria kept only peer-reviewed articles (e.g., Leonidou et al., 2020; Battisti et al., 2021; Vrontis et al., 2022) and discarded 36 documents. Then after a full-text review, 59 non-pertaining articles that did not exactly match the topic (Pascucci et al., 2018; Leonidou et al., 2020; Battisti et al., 2021; Vrontis et al., 2022) were discarded due to the ex-post exclusion criteria (tab. 2.1), leaving the final sample of 32 articles published from 2015 to early 2022 (fig. 2.2).

2.3.3 Data extraction form

All articles of the final sample were downloaded (Vrontis et al., 2022) and content analysis was carried out manually by the authors (Battisti et al., 2021). After a first set of

[1] Search strings: ("equity" AND "crowdfunding" AND "success"); ("equity" AND "crowdfunding" AND ("failure" OR "unsuccessful")).

inspective full-text reviews, the articles were coded and classified in a data extraction form (Pascucci et al., 2018; Vrontis et al., 2022; Battisti et al., 2021). We collected data into Microsoft Excel Spreadsheets (Vrontis et al., 2022; Battisti et al., 2021) mainly on: i) definitions, ii) theoretical background, iii) hypothesis, iv) methodologies, v) platforms investigated, vi) variables, vii) size (no. of startups analyzed) of the samples, viii) and finally main findings.

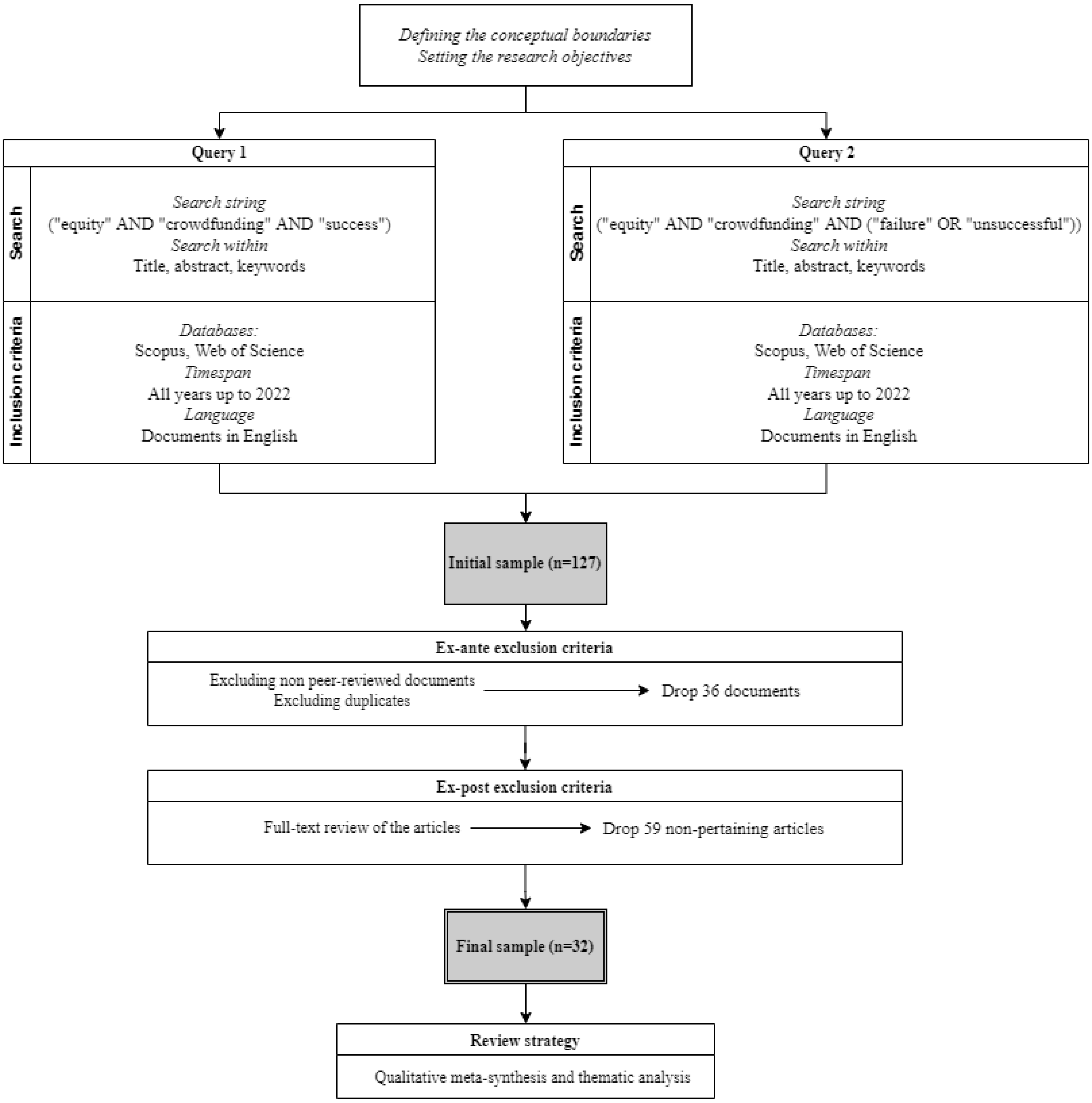


Figure 2.2: steps in the systematic literature review

2.3.4 Bibliometric analysis

Bibliometrics is a method of analysis that uses mathematical and statistical techniques to quantitatively analyze information about references and publications (Broadus, 1987). It is a concrete tool to provide an accurate and objective view on the state-of-the art of a specific literature, synthetize quantitatively the main descriptive information and gives hints about possible trends of further research (Diodato and Gellatly, 2013).

In this work, bibliometrics analysis was conducted through Bibliometrix, which is a tool developed by Aria and Cuccurullo (2017) as a package for the R-Project software for statistical computing. It provides data analysis and mapping by observing patterns, associations, co-occurrences, and relationships among the authors, topics, keywords and institutions within the references.

2.4 Findings

2.4.1 Descriptive analysis of the sample

In this section we present the main descriptive statistics to provide an initial map of the extant literature and to recognize possible gaps for future lines of research (Battisti et al., 2021). The descriptive analysis was conducted using the "Bibliometrix" package developed by Aria and Cuccurullo (2017) in R language to analyze the data and illustrate the findings.

Authorship, sources and affiliations analysis: relevance, citations, network and geographical location

The resulting sample is made up of 32 articles (tab. 2.2) that were chosen from 22 different journals in the period 2015-2022. Six articles are single authored, though the majority is multi-authored, with 70 authors involved as a whole from institutions and 2.19 authors per document, showing in any case a large community of academics involved in the issue.

The progression of the annual scientifical production demonstrates that the field of research on ECF is very recent and fast-growing (fig. 2.3). The findings for 2021 and 2022 may be not representative as articles are in progress or were not yet published before this study (February 2022).

Figures 2.4a and 2.4b show respectively the twenty most relevant authors, in terms

MAIN INFORMATION ABOUT DATASET	
Timespan	2015:2022
Sources (Journals, Books, etc)	22
Documents	32
Average years from publication	3.34
Average citations per documents	62.91
Average citations per year per doc	10.86
References	1668
AUTHORS	
Authors (N.)	70
Author Appearances	85
Authors of single-authored documents	5
Authors of multi-authored documents	65
AUTHORS COLLABORATION	
Single-authored documents	6
Authors per Document	2.19
Co-Authors per Documents	2.66
AFFILIATIONS	
Institutions	45

Table 2.2: Descriptive statistics of the sample

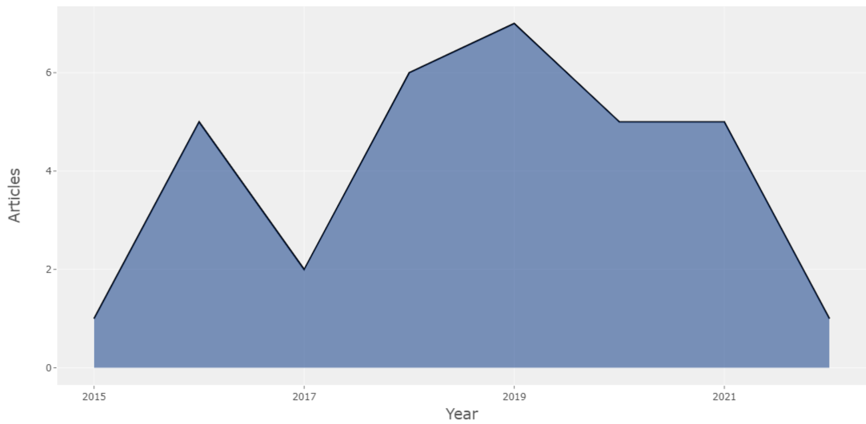
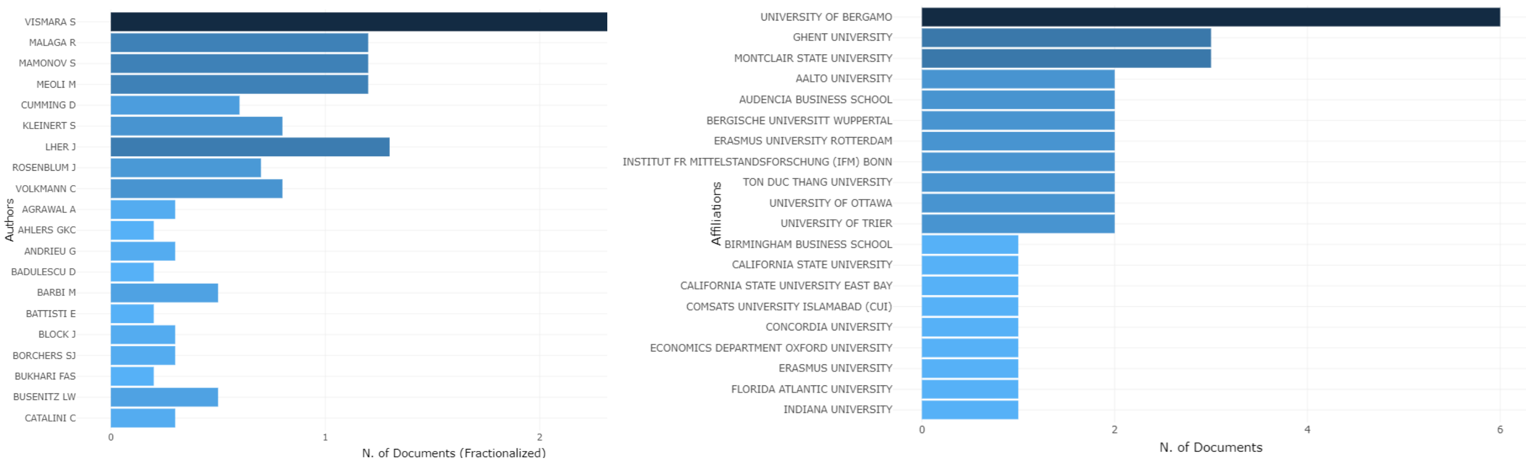


Figure 2.3: Annual scientific production

of number of articles authored fractionalized, and the twenty most relevant institutions within the sample.

Figure 2.5 shows, instead, the twenty most globally cited articles of the sample. The study from Ahlers et al. (2015) appears to be the most cited as it represents the bedrock of signaling theory in ECF, followed by one of the articles of Vismara (2016) on equity retention in ECF.

Figure 2.6 presents the country collaboration world map and geographical location of the studies within the sample. The darker color exhibits a more intense article production. Italy appears to be the fulcrum of worldwide collaborations, in line with findings from figures 2.4a and 2.4b.



(a) Most relevant authors (b) Most relevant affiliations

Figure 2.4: Most relevant authors and affiliations

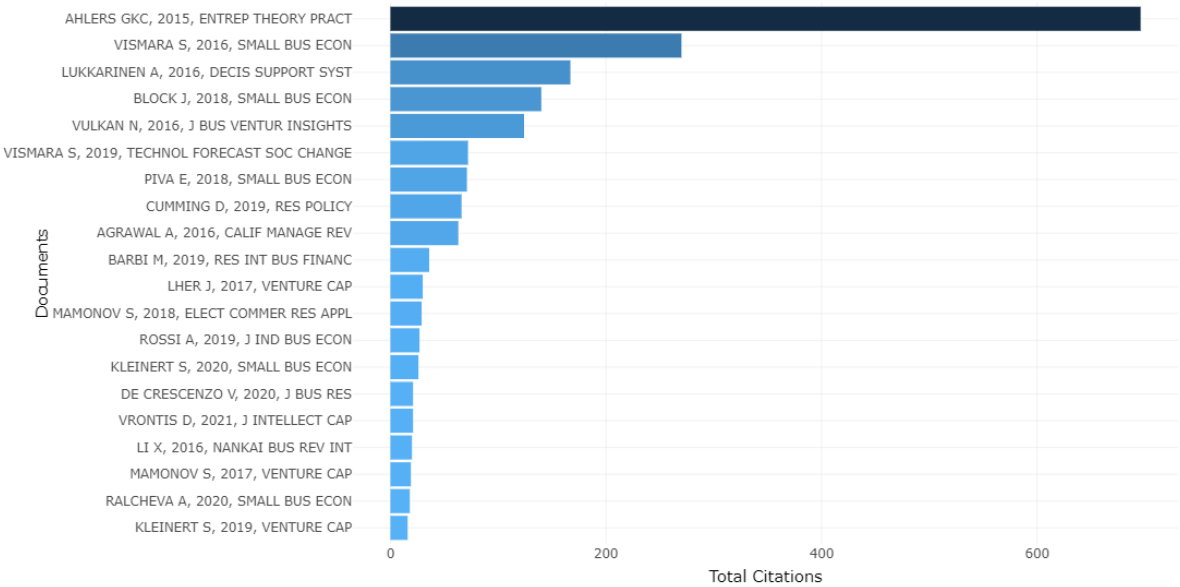


Figure 2.5: Most cited articles

Platforms

Most of the articles in our sample are based on studies of British equity crowdfunding platforms: above all Crowdcube and Seedrs (Tab. 2.4.1). The rationale lies in the large set of data available, compared to other platforms, about the campaign, startup, and the investors. The majority are single-platform studies, and seven of them are multi-platform, meaning that the dataset is composed of campaigns from more than one platform. Only two multi-platform studies are based on platforms of different nationalities, allowing possibly to capture geographical and cultural heterogeneities.

Methodologies and techniques

Most methodologies and investigation techniques adopted to analyze the data are quantitative, but there is a recent positive trend towards qualitative or quali-quantitative

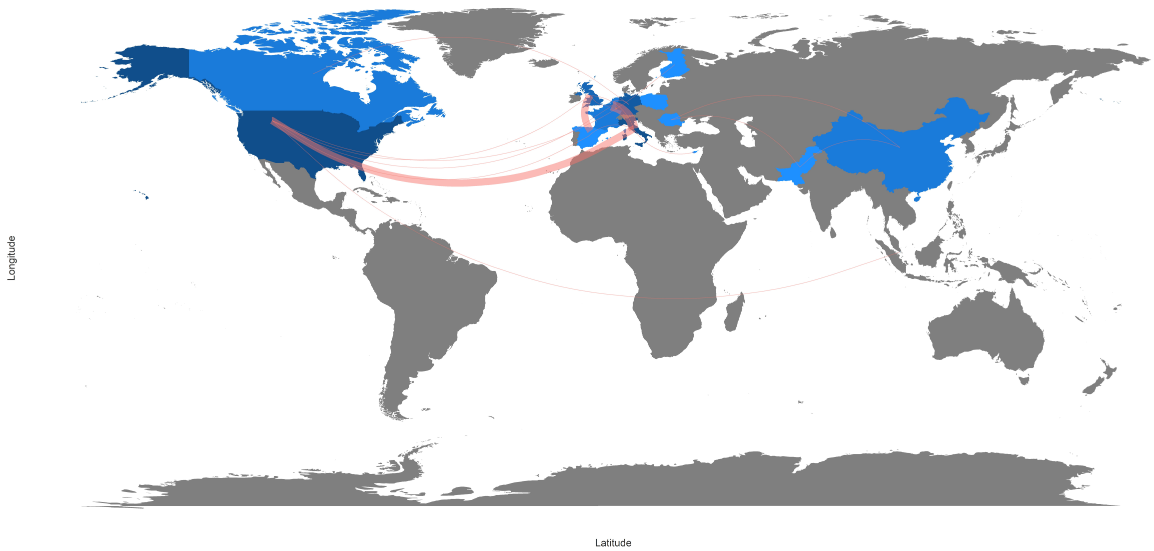


Figure 2.6: Country collaboration map

approaches which allows to capture deeper and softer pieces of information by directly analyzing the agents of the process. Qualitative studies are mostly based on interviews, case studies and content analysis. Quantitative works are mostly based on multivariate analysis (OLS, logistic and negative binomial regressions) except for one which is univariate and implements a mean difference statistic. Multivariate analysis studies the joint effect of multiple explanatory variables to a dependent variable. Above all, OLS regressions are commonly adopted in the case of a metric dependent or log-dependent variable (i.e. capital raised). Negative binomial and zero-inflated negative binomial regressions are adopted for over-dispersed data and to account for excess zeros (i.e. number of investors). Logistic or logit regressions, instead, for model binary dependent variables (i.e. success/failure of a campaign). Survival models are then essential to evaluate dynamically the impact on the speed of capital allocation.

Recently, De Crescenzo et al. (2020) adopted a fuzzy-set Qualitative Content Analysis as an example of quali-quantitative technique which mixes the two families of methodologies.

Table 2.3: Sample overview

Authors	**Platforms and countries**	**Methodologies and techniques**	**Dependent variables**	**Investment speed**	**Panel dataset**
Ahlers et al. (2015)	Australian Small Scale Offerings Board (ASSOB) (Australia)	Univariate: Mean differences, Multivariate: zero inflated negative binomial regressions, OLS, survival analysis (exponential hazard models)	Fully funded, Number of investors, Funding amount, Speed investment	Yes	
Agrawal et al. (2016)	AngelList (USA)	Qualitative			
Li et al. (2016)	Dajiatou (China)	ELM, Independent-sample t-test, K-means cluster, linear regressions	Ratio of fundraising completion, Fundraising speed, Number of followers	Yes	
Lukkarinen et al. (2016)	Invesdor (FIN)	Multiple linear regressions	Amount raised, Number of investors		
Vismara (2016)	Crowdcube, Seedrs (UK)	Negative binomial regression; OLS	Percentage of funding, Number of investors		
Vulkan et al. (2016)	Seedrs (UK)	Linear probability model, OLS, Quantile regression	Success dummy, Percentage raised, Shares of goal covered in Week 1	Yes	
Löher (2017)	Companisto, Fundsters, Innovestment, Seedmatch and Bergfürst	Qualitative: Semi-structured interviews			
Block et al. (2018)	Seedmatch and companisto (GER)	Fixed effects negative binomial, OLS panel regression	Number of investments, Capital raised	Yes	Yes
Löher et al. (2018)	Companisto, Fundsters, Innovestment, and Seedmatch (GER)	Quali-quantitative: Interviews, OLS	Funding Level (percentage of funding)		
Malaga et al. (2018)	USA	Exploratory analysis			
Mamonov and Malaga (2018)	16 platforms from USA	Logistic regression	Success binary		
Motylska-Kuzma (2018)	Beesfunds, Crowdway, Findfunds (POL)	Non-parametric correlation tests	Amount of raised funds, Success rate, Number of contributors		
Piva and Rossi-Lamastra (2018)	SiamoSoci (ITA)	Probit	Success binary, Percentage of funding, Number of investors		
Barbi and Mattioli (2019)	Crowdcube (UK)	Univariate and multivariate models (OLS)	Capital raised, Number of investors		
Cumming, Meoli, et al. (2019)	Crowdcube (UK)	First stage: bivariate, probit regression. Second stage: generalized structural equation model (GSEM)	Success binary		
Kleinert and Volkmann (2019b)	Crowdcube (UK)	Qualitative: codebook; Quantitative: Poisson regression	Funding Raised		Yes

Mamonov and Malaga (2019)	Crowdfunder (Los Angeles)	Logistic regression models	Success, Partial success		Yes
Nitani et al. (2019)	Crowdcube (UK), Invesdor (FIN), Companisto (GER), and FundedByMe (SWE)	OLS, Logistic regression and Survival models (proportional hazards models)	Fundraising success (binary), Funding speed, Capital raised	Yes	
Rossi et al. (2019)	185 platforms	Negative binomial regressions	Platform success		
Usman et al. (2019)	Crowdfunder (UK)	Logistic regression, Tobit regression	Success binary, Number of backers, Funding amount		
Vismara (2019)	Crowdcube and Seedrs (UK)	Probit regressions, Negative binomial regression	Success binary, Number of investors, Presence of professional investors		
De Crescenzo et al. (2020)	Crowdcube (UK)	Fuzzy-set Qualitative Comparative Analysis	Success binary, Failure binary		
Kleinert et al. (2020)	Crowdcube (UK)	Negative binomial and Logit regressions	Success binary, Number of investors		
Ralcheva and Roosenboom (2020)	Crowdcube and Seedrs (UK)	Logistic regressions	Success binary		
Xiao (2019)	AngelCrunch (China)	Qualitative: interviews			
Lim and Busenitz (2020)	Crowdfunder (Los Angeles)	Zero-inflated negative binomial and normal negative binomial regressions	Funding Raised		
Shafi (2021)	Crowdcube (UK)	Probit regressions, OLS	Success, Amount raised		
Andrieu et al. (2021)	Wiseed, Smart Angels, Sowefund, Anaxago (FRA)	OLS regression, Iteratively Reweighted Least Squares, Propensity Score Matching	Percentage of funding		
Dority et al. (2021)	Alchemy Global, AngelList, Crowdfunder, EarlyShares, EquityNet, MicroVentures, OneVest, OurCrowd, Return on Change, Seed Equity, SeedInvest, WeFunder. (USA)	Sentiment analysis; Tobit regression	Percentage of funding		
Meoli and Vismara (2021)	EquityCrowd (name disguised, country unknown)	Probit regression (other empirical settings also: Panel Poisson, Panel Negative Binomial regressions)	Success binary		
Vrontis et al. (2020)	21 Italian platforms	Social Network Analysis, Panel OLS regression	Success ratio of platforms		Panel
Coakley et al. (2022)	Crowdcube, Seedrs, SyndicateRoom (UK)	OLS, Probit regressions	Success binary, Capital raised, Overfunding		

Quantitative variables

Three target variables are mostly recurrent: the success binary variable, number of investors and capital raised. The former is a dichotomous variable that assigns the value of 1 in case of success of a campaign, which is defined as the achievement of the minimum funding target, and 0 otherwise. The latter are two variables that capture respectively the number of backers at the end of a campaign and the amount of financing that has been raised in total, which are absolute values of performance. Recent literature has focused on more comparable ways such as relative measures. Percentage of funding above all relates the capital raised to the minimum funding goal and does not rely on the size of a new venture nor on its funding goal, allowing comparisons between campaigns. An innovative way to measure success is the investment speed. It relates the capital raised to its timing, proving the ability of entrepreneurs to attract funds effectively. However, some authors measure it as a simple ratio between capital raised and duration of a campaign, while others adopt survival models of analysis, which confer dynamism. Authors have

Conceptual categories	**Independent variables addressed**
Social capital	Number of non-executives board members, LinkedIn presence, Facebook presence, Twitter presence, Information HUB role of platform
Digital-related features	Social media usage, Project updates, Digital interaction, Online presence, Featured in media, Featured in newspapers/tv.
Team characteristics	Team size, Gender diversity, Tenure heterogeneity, Age heterogeneity, Management rating, Lone founder, Team board/employees size.
Intellectual capital	Patents, Property rights, Value added intellectual coefficient (VAIC).
Firm characteristics	Firm maturity, Ratio of full-time workers, Location, Venture with large clients, B2B clients, Product development stage, Big city location, Seed stage.
Financial measures	Sales, External financing, Presence of financial information, Expected sales growth, Expected EBITDA, Absence of disclaimer of no financial information.
Campaign round characteristics	Share price, Campaign duration, Target capital, equity offered, Reward/discounts in addition, Exit strategy, Exit IPO, Exit M&A, Usage of funds, Tax relief, Shares accumulated in first week, Largest investment.
Investors' characteristics	Number of investors, Professional investors, VC, BA, Early led investments, percentage of lead investors' investments, Investor frequency, Public profile of investors.
Business characteristics	High-tech, B2B, Sustainability, Industry sector, Business development, Market risk, Business rating, Market rating, Product rating, Competition rating.
Project description and presentation	Use of pitch videos, Presence of entrepreneurs in pitch, Presence of pictures, Length of description, Readability, Word count, Tone, Proxemics and Attitude.

Table 2.4: Categories of explanatory variables

looked at different categories of explanatory variables. Table 2.4 shows that the ones most frequently addressed are those connected to the founders' and firm's characteristics.

Human capital collects available information about the quality of education of the team members, their prior crowdfunding experience and prior experience in the industry.

Social capital refers to the dimension of valuable interpersonal relationships of entrepreneurs and firms. The dimension of the social media network is an important indicator of visibility and self-marketing both for entrepreneurs and firms, especially in a digital environment such as ECF.

Another set of variables of interest concerns the characteristics of the team as a whole: team size, gender diversity, team's age and intellectual capital.

New ventures' characteristics, also used as control variables, are mainly: firm's age and maturity, the geographical location, which affects investors' willingness to invest both regarding geographical and cultural influence and regarding the distance from the investors and a home bias effect, and the disclosure of relevant financial information, such as financial KPI, debt size and credit rating scores.

Campaign characteristics generally act as signals of good quality or self-confidence of entrepreneurs for investors. The percentage of shares offered represents the proportion of shares released to the crowd at the end of the campaign. The minimum funding goal is the target floor of capital to be reached to achieve campaign success. The maximum funding goal is the cap of capital that could be raised to avoid dilution of the control shares of entrepreneurs. The minimum investment captures the price of a single share. The campaign duration represents the time window for investments. The presence of professional investors reveals that an investment institution believes in the projects and supports it, often with larger resources. The pre-money valuation provides an estimate of the value of the new venture before obtaining equity crowdfunding financing. The anticipation of an exit strategy for the investments, such as buy-back strategies or the buy-out from an institutional counterpart, ensures the crowd about liquidity of the asset. Finally, other variables taken into consideration concern taxation incentives, voting rights, share type and the number of followers and people interested in the project.

Authors also analyzed business characteristics, competition and industry sectors. The participation in a high-tech industry sector is perceived as a signal of the innovation degree of a startup.

Alternative variables are found within the description of projects, length and understandability of the description, presence of quality pictures, presence and length of pitch-videos, proxemics and attitude of the entrepreneur, comments and questions made on the web by interested backers, as well as frequency and timing of updates and answers provided by the founders.

2.5 Meta-synthesis and integrative framework

2.5.1 Definition of equity crowdfunding

Despite its recent development and its increasing dissemination in literature, the definition of ECF is not unanimous, however five commonalities emerge from a qualitative synthesis of the articles. Firstly, we find the relevance of funding by the crowd and the ultimate target, that is raising money. So, the equity-based model is basically an 'alternative' method for funding a business. The second characteristic lies in the innovativeness and digital nature of this form of business financing, compared to more traditional ones, based on a Fintech environment (Cumming, Meoli, et al., 2019) since it allows the issuer to reach a wider audience and, on the flipside, it allows even smaller and unsophisticated investors to participate and provides more efficient access to information. The U.S. SEC defines equity crowdfunding as the *"process of raising funding via the internet in exchange for securities"* (Securities, Commission, et al., 2016), highlighting that the web-based feature is a key point. Inevitable deduction is a different attitude of nascent entrepreneurs towards digital instruments to leverage on their catchment area of potential investors and customers (Scarmozzino et al., 2017). Thirdly, ECF mainly refers to the early stages of a firm's development, although a campaign could be launched by a mature firm as well. Fourthly, the main distinctive characteristic of this model lies in the return scheme. The compensation for the backers is not reward-based, but rather stock-based, where each investor receives a portion of the firm's shares and participates in its equity. The fifth characteristic concerns the dimension of investors, who are mostly small investors and private individuals, even if lately there has been an increasing interest and presence of professional investors; this happens for the signaling effect that gives credibility to the crowd and enhances the probability of reaching the minimum funding target (Cumming, Meoli, et al., 2019).

2.5.2 Integrative theoretical framework

Our qualitative meta-synthesis (Tranfield et al., 2003), supporting response to our research question, identifies four main clusters of disciplines and provides a taxonomy of the main theories, addressed within traditional finance, behavioral economics, corporate finance and entrepreneurship (tab. 2.5).

The predominant framework belongs to traditional finance theories and, mainly, to the signaling theory. Recalling that our sample is focused on the outcome of campaigns, the signaling theory has been used by papers analyzed to investigate signals for the effective quality of projects, reduction of information asymmetries and thus persuasion of investors to fund campaigns. Several authors have also investigated the phenomenon of informational cascade, where an investor's decision is based on the inference about other people's set of information and might result in an imitative behavior (Vismara, 2018).

It appears inevitable that the exploration of behavioral drivers affecting the decision-making process of investors, and behavioral topics are usually drivers for ECF outcome. Some authors adduced theoretical support from literature regarding investor rationality, decision theory and herding behavior. Investors derive their choices from several aspects other than financial information and are likely prone to be affected by cognitive biases and decisional shortcuts. Herding behavior is quite common in contexts of asymmetric information (Scharfstein and Stein, 1990), where the decision-maker follows the crowd and invests in a specific startup only after having learned that the campaign is about to conclude successfully. Additionally, crowd-investors tend to evaluate more heavily those characteristics that are more easily understood due to the so-called "less-is-better effect", where decision makers facing a high variety of information are subject to a cognitive distortion known as "evaluability heuristic" (Hsee, 1998). Any outcome of a crowdfunding campaign is definitely evaluated from the business plan and financial characteristics of the new venture. Thus, corporate finance literature gives support to the research for driving factors of investing decisions. A wide set of theories concerning the firm and its governance (i.e. ownership and commitment) accompanies these studies.

Similarly, an entrepreneurial framework allows to understand the impact on the outcome of characteristics related to the entrepreneur and the team of founders. Traditional literature about entrepreneurship however could result in being outdated in a digital and innovative environment such as equity crowdfunding, where an entrepreneur must find different ways to promote her/his business, and sometimes must reinvent her/his role. Hence, literature is currently adapting to gain a deeper understanding of the digital-related dynamic skills requested to cope with these frontier phenomena.

2.6 Thematic analysis and longitudinal reporting

From a thematic analysis (Tranfield et al., 2003; Braun and Clarke, 2006; Webster and Watson, 2002), emerging key themes and dominant concepts of studies included in our sample can be organized according to different categories of determinants of the outcome of an ECF campaign (tab. 2.6). These elements represent expression of signals that are sent/perceived by entrepreneurs/investors to reduce the informal asymmetries that are inevitable in any financing deal, affecting success, or failure, of the ECF operation. Note that each category follows a chronological order of papers to provide a longitudinal review, whenever possible, because it is reasonable to suppose that research should contribute by adding to the existing findings. Nevertheless, this diachronicity is sometimes denied because papers combine multiple perspectives.

Firm characteristics

Most of the literature on ECF success focuses on the characteristics of new ventures. In fact, firm age or development stage has an uncertain effect on ECF (Shafi, 2021). Early-stage firms might be less likely to attract financing (Li et al., 2016; Mamonov and Malaga, 2018, Mamonov and Malaga, 2019; Barbi and Mattioli, 2019). At the same time, investors could be unicorn-seeking and looking for young innovative companies with unexplored potential (Nitani et al., 2019; Vismara, 2019; De Crescenzo et al., 2020; Ralcheva and Roosenboom, 2020).

Some authors assume that ventures with headquarters in big cities could attract more investors and have addressed the geographical location as a dummy variable, but the effect is not significant (Vismara, 2016; Barbi and Mattioli, 2019; Shafi, 2021).

Firm's pre-money valuation, even though not extensively investigated in literature, might positively affect the ECF outcome (Löher et al., 2018).

Recently, research has begun to investigate the effect of client portfolio of a firm and found a significant positive effect for those that have large corporate (B2B) clients (Mamonov and Malaga, 2018; Mamonov and Malaga, 2019). A study by Ralcheva and

Roosenboom (2020) is the first to investigate the attendance of acceleration programs from new ventures prior to an ECF campaign and it found that they are more likely to be funded.

Financial information and measures

Apparently, in contrast with stock market investments, and with a general idea that financial information about the firm can reduce information asymmetries, the quality of this information appears not to be relevant (Ahlers et al., 2015; Lukkarinen et al., 2016), maybe due to the different size/dimension, financial education and competencies of investors (Shafi, 2021). In particular, one of the first studies of our literature found that the absence of financial information is not perceived negatively by investors, unless the entrepreneur did not provide a disclaimer for it (Ahlers et al., 2015). Others demonstrate that investors seem to pay only scarce attention to financial information due to the perceived difficulty of understanding it (Shafi, 2021).

More recent literature has focused on financial information related to revenues and sales, which are a more understandable measure of venture performance, and found that firms with good sales ratios and capable of already generating revenues at the time of their campaign, have more probabilities of getting funded (Cumming, Meoli, et al., 2019; Nitani et al., 2019; Kleinert et al., 2020).

Note that an essential financial indicator for investors is the financial commitment and ownership of the entrepreneurs. In fact, higher own commitment increases investors' willingness to invest (Ahlers et al., 2015; Cumming, Meoli, et al., 2019; Shafi, 2021). According to some authors, financial commitment is the single most important determinant in explaining crowdfunding success (Vismara, 2016; Löher et al., 2018). Cumming, Meoli, et al. (2019) add that family businesses, although apparently less attractive for small investors, have lower chances of failure by being long-term oriented and thus are considered to be relatively safer investments.

On the contrary, a higher percentage of shares offered to the crowd has a negative strong relationship to the success of a campaign (Vismara, 2019; Ralcheva and Roosenboom, 2020), because investors appear to be discouraged by entrepreneurs who tend to give away larger ownership (and commitment) of their company, thus forcing crowd-investors to bear a large part of the entrepreneurial risks.

In line with this issue, a venture that obtained early-stage financing, in the forms of venture capital or business angels, prior to the campaign or the issuing of a follow-on ECF round, delivers a positive signal to investors (Mamonov and Malaga, 2018; Barbi and Mattioli, 2019; Shafi, 2021; Kleinert et al., 2020; Ralcheva and Roosenboom, 2020).

Recently, Nitani et al. (2019) were the first to investigate the purpose of usage of ECF funding and show that entrepreneurs who declare using funding as working capital attract more funds, rather than declaring marketing, R&D or market expansion purposes.

Intellectual capital and patents

Intellectual capital, and specifically the possession of patents or property rights, is a controversial factor that has been investigated since the start of ECF literature. Although it should be a signaling technique that proves the quality of intangible assets, and thus should foster crowd-investing (Piva and Rossi-Lamastra, 2018; Mamonov and Malaga, 2019), surprisingly many authors found instead that it does not affect the outcome of a campaign (Ahlers et al., 2015; Mamonov and Malaga, 2018; Ralcheva and Roosenboom, 2020).

A very recent study from Vrontis et al. (2020) measured the intellectual capital using the Value Added Intellectual Coefficient (VAIC model), as the sum of three components: capital employed, human and structural efficiencies. The results assert its positive impact on the success rate of ECF campaigns.

Business characteristics and project description

Lukkarinen et al. (2016) found that the understandability of a project impacts significantly and positively on the chances of success. In particular, Shafi (2021) affirms that investors may have difficulties to evaluate team characteristics and financial information but may find business characteristics easier to evaluate and can form personal opinions about the desirability of certain consumer products and thus market expectations. In relation to this issue, according to the "less-is-better effect" and to the evaluability heuristic, investors tend to attribute more importance to fewer and more understandable pieces of information (Hsee, 1998).

Topic	Theory/sub-topic	Articles
Traditional finance	Signaling theory	*Ahlers et al., 2015; Vismara, 2016, 2019; Vulkan et al., 2016; Block et al., 2018; Piva and Rossi-Lamastra, 2018; Barbi and Mattioli, 2019; Kleinert and Volkmann, 2019; Nitani et al., 2019; Rossi et al., 2019; Usman et al., 2019; De Crescenzo et al., 2020; Kleinert et al., 2020; Ralcheva and Roosenboom, 2020; Lim and Busenitz, 2020; Dority et al., 2021; Vrontis et al., 2021b; Meoli and Vismara, 2021; Coakley et al., 2022*
	Information asymmetry	*Agrawal et al., 2016; Löher, 2017; Löher et al., 2018; Piva and Rossi-Lamastra, 2018; Kleinert and Volkmann, 2019; Nitani et al., 2019; Rossi et al., 2019; Usman et al., 2019; Dority et al., 2021*
	Principal-agent theory	*Mamonov and Malaga, 2018, 2019; Cumming et al., 2019*
	Capital markets and information disclosure	*Li et al., 2016; Block et al., 2018*
	Intermediation	*Löher, 2017; Malaga et al., 2018; Rossi et al., 2019; Xiao, 2020*
Behavioral economics	Decision theory	*Lukkarinen et al., 2016; Mamonov and Malaga, 2018*
	Herding behaviour	*Vulkan et al., 2016; Kleinert and Volkmann, 2019; Nitani et al., 2019; Meoli and Vismara, 2021*
	Information cascade	*Vismara, 2016; Kleinert and Volkmann, 2019; Meoli and Vismara, 2021*
	Investor rationality	*Nitani et al., 2019; Vismara, 2019*
	Knowledge sharing	*Vrontis et al., 2021b*
	Information understandability	*Lukkarinen et al., 2016; Block et al., 2018; Dority et al., 2021*
	Information manipulation	*Meoli and Vismara, 2021*
Corporate finance	Evaluability theory	*Shafi, 2021*
	IPOs and SEOs	*Ahlers et al., 2015; Vismara, 2016; Nitani et al., 2019*
	Ownership and commitment	*Ahlers et al., 2015; Vismara, 2016; Löher et al., 2018; Cumming et al., 2019; Rossi et al., 2019*
	Tax incentives/Taxation benefits	*Vismara, 2016, 2019; Vulkan et al., 2016; Shafi, 2021*
	Trust theory	*Xiao, 2020*
	Voting rights	*Agrawal et al., 2016; Cumming et al., 2019; Rossi et al., 2019*
Entrepreneurship	Computer mediation challenge	*Lukkarinen et al., 2016; Piva and Rossi-Lamastra, 2018; Mamonov and Malaga, 2019; Usman et al., 2019; Nitani et al., 2019*
	Contingency theory	*De Crescenzo et al., 2020*
	Entrepreneurial finance	*Lukkarinen et al., 2016; Vulkan et al., 2016; Löher et al., 2018; Mamonov and Malaga, 2018; Barbi and Mattioli, 2019; Kleinert and Volkmann, 2019; Shafi, 2021; Kleinert et al., 2020; Ralcheva and Roosenboom, 2020; Xiao, 2020*
	Gender	*Malaga et al., 2018; De Crescenzo et al., 2020; Andrieu et al., 2021*
	Human capital	*Piva and Rossi-Lamastra, 2018; Barbi and Mattioli, 2019; Kleinert et al., 2020; Lim and Busenitz, 2020*
	Network and social capital	*Vismara, 2016; Nitani et al., 2019; Usman et al., 2019; Kleinert et al., 2020*
	Risks in entrepreneurship	*Mamonov and Malaga, 2018, 2019*
	Sustainable entrepreneurship	*Motylska-Kuzma, 2018; Vismara, 2019*

Table 2.5: Predominant theoretical framework

Table 2.6: Structure of the thematic analysis

Authors	Theoretical framework	Categories of determinants of ECF	Mechanisms through which they affect ECF	Variables that can affect ECF outcome and effect sign
Ahlers et al., 2015	Signaling theory, Entrepreneurial Ownership, IPO	Human capital, Social capital, Intellectual capital, Financial information	Signals	Human capital (+): board members (+), %MBA (+). Social capital (+/-): %non-executive board members. Intellectual capital (+/-): patents. Retained equity offering (-). Financial information: absence of disclaimer of no information (-; but not on number of investors). Exit channel/strategy (+/-; "cheap talk" and not effective signal)
Agrawal et al., 2016	Information asymmetry and quality assessment; Voting rights and syndicates	Syndicates	Syndicates deals provide division of labour among investors (due diligence, etc.), enhance economic growth by reducing market failures and allocating capital more efficiently	Syndicates (+)
Li et al., 2016	Traditional finance on capital markets and information disclosure	Firm characteristics, Team characteristics, Lead investor information, Project presentation and Social interaction	Likelihood of elaboration (ELM) and persuasion; Information disclosure reduce information asymmetry and induce persuasion; Early lead investments as signal, but not for higher percentage of investment (collusion risk)	Team size (+), Firm age (+), Ratio of full-time workers (+), Human capital (+), Project updates and interactions (+), Pitch video (+), Length of description (+), Information disclosure (+), Early lead investments (+), Percentage of lead investors' investments (-; think they might collude to attract followers)
Lukkarinen et al., 2016	Drivers of investment decisions in adjacent fields to ECF: crowdfunding (reward, etc.) and VCs and BAs	Investment decision criteria of CF, Investment decision criteria of early-stage financing (VC, BA), Campaign characteristics	Credibility, Encourage investment, Capability and decisiveness of entrepreneurs	1) BA/VC criteria (+/-): financial information (+/-, but may be relevant for accredited investors with more expertise). 2) CF criteria (+, easily observable): Understandability of product (+), Campaign characteristics (+): (funding target (+), share price/min investment (-), campaign duration (-), Financials provision (+/-)), Network (+): (private funding from early hidden phase (+), social media network interaction (+, Facebook))
Vismara, 2016	Equity retention, entrepreneurs' social capital and social network	Campaign characteristics, Social capital, Firm characteristics	Signaling	Social capital (+, LinkedIn), Retained equity offering (-), Team size (+), Funding target (+), tax incentives (+/-), Exit IPO (+/-), Exit in 5 years (-), Dividends intention (+), Female gender (-), duration (-), Seedrs (+), London (+/-)
Vulkan et al., 2016	Crowdfunding	Campaign characteristics, Investors characteristics, Firm characteristics,	Herding behaviour, Signaling	Share accumulated in first week (+), Funding target (-), Largest investment made by single investor (+), Number of investors (+), Premoney (+/-), Team size (+, weak), Tax incentives (+/-), Public profile of investors (+/-)

Löher, 2017	Crowdfunding, Role of platforms, Information asymmetries, Intermediation	Role of platforms	Platform intermediation: Project evaluation and assessment (pre-screening), Reputation, Reduction of information asymmetry, Reduction of transaction costs	Platform intermediation (+)
Block et al., 2018	Signaling theory and information disclosure	Updates, Readability/understandability index of updates	Updates by start-up as signals in ECF	Update number (+, but takes time and "cheap talks" issue), Flesch readability index (+, but weak, on number of investments only and takes time), Word count (+/-). Updates about: (New funding (+), Business development (+), campaign developments (+), cooperation projects (+), Team update (+/-, typically do not change during campaign), Business model (+/-, typically do not change during campaign), External certifications (-, not credible?)
Löher et al., 2018	Entrepreneurial finance, Information asymmetry, Crowdfunding	Own commitment level of entrepreneurs, Firm characteristics, Campaign characteristics, Investor characteristics	Signals	Own commitment level (+), premoney(+), professional investors (+/-), Firm age (-), Financing alternatives available before start (+/-), Destination of funds: (market entry (+/-), market penetration (+/-)).
Malaga et al., 2018	Female entrepreneurship and finance	Gender	ECF platform as facilitator for female entrepreneurship	Gender (+/-, perhaps ECF do not ease female entrepreneurship)
Mamonov and Malaga, 2018	ECF title III JOBS Act	Business characteristics: Market risk, Execution risk, Agency risk. Human capital, Intellectual capital, Firm characteristics.	Less sophisticated investors will follow more sophisticated investors' lead (BA, VC) decision making	Company development (of product) stage (+), Venture with large corporate clients (+), Intellectual capital and patents (+/-), Team size (+), Prior early-stage funding (+, BA, VC), Serial entrepreneur (+/-), Entrepreneur experience (+/-)
Motylska-Kuzma, 2018	Sustainable development	Sustainability elements, Campaign characteristics	Sensitivity of investors to sensitivity	Key elements of sustainable development (+, but not on number of investors), Basic elements (+, weaker: number of investors not sensitive to sustainability)
Piva and Rossi-Lamastra, 2018	Information asymmetry, Human capital, Signaling	Human capital, Social Capital, Intellectual capital, Firm characteristics, Business characteristics	Signals	Entrepreneur social (media, LinkedIn) capital (+), Funding goal (-), High-tech (-, more uncertainty Ahlers et al 2015), Team size (+/-), Intellectual capital and patents (+). Human capital: (entrepreneur education (+, but only specific to business education; others are +/-), Entrepreneur experience (+, but not necessarily in industry)). Gender (+/-),

Barbi and Mattioli, 2019	Human capital, Crowdfunding	Human capital, Firm characteristics, Team characteristics, Business characteristics	Signals	Firm age (+), High-Tech (+/-), Big city (+/-), Reward/discounts in addition to shares (+/-), Prior seed financing (+), Featured in media, Newspapers, TV (+), Online presence (+/-, Number of social media on webpage), Team size (+), Graduate within team (+, weak), Professional business experience (+), Experience in the field of firm (+/-), Gender (+/-), Volunteering (+/-)
Cumming et al., 2019	Corporate finance theories about voting rights and separation between ownership and control (Principal-Agent)	Ownership variables	Signals: firm value increase with cash-flow rights of controlling shareholders but decrease if voting rights exceed cash-flow rights. Separation of voting power and cash-flow	Equity offered (-, equal to cash-flow rights (+)), Separation ownership and control (-, potential rise of agency costs), Separation mitigated by entrepreneur experience (+), Firm age (-), Positive sales (+)
Kleinert and Volkmann, 2019	Information asymmetries, Early-stage finance	Discussion and discussion topics. Control for herding (investor frequency before day t)	Signals, herding	Investor frequency (+), Competing offers (+), Entrepreneur reply (+), Updates (+), Discussions (+), Discussion topic (+, significant: market risk, Financial snapshot, Likely return, shareholders' rights)
Mamonov and Malaga, 2019	Market risk, Execution risk, Agency risk, Computer mediation challenge (videos)	Intellectual capital, Human capital, Firm characteristics, Market/product characteristics, Pitch video	Effects of market risk, agency risk, execution risk and computer mediation	Market risk: Firm age/stage (+), B2B corporate clients (+), Patents (+). Agency risk: BA/VC investors (+). Execution risk: Team size (+/-), Entrepreneur industry experience (+/-), Serial entrepreneur (+). Computer mediation: use of pitch video (+), presence of entrepreneur in video (+/-)
Nitani et al., 2019	Information asymmetry, Crowdinvestors' rationality, Social media herding behavior	Firm characteristics, Financial information and measures, Usage of funding, Social capital, Human capital	Signals, Herding	Firm attributes: Firm size (+), Firm age (-), Exit strategy: IPO (+), M&A (-, weak). Usage of funds: Working capital (+), R/D (+/-), Marketing (+/-), Market expansion (+/-). Financial measures: Expected sales growth (+, but reasonable), Expected EBITDA (+). Social network (+, LinkedIn and Facebook). Prior start-up experience (+). Education degree (+/-)
Rossi et al., 2019	Corporate governance: Separation between ownership and control, Voting rights, Information asymmetry	Ownership and voting rights, Syndicate-platform, Platform characteristics	Signals: Impact of voting rights delivery, Platform intermediation	Voting rights (+/-): Individual voting rights (-), Pooled voting rights (+/-), Syndicate-like platforms (-), Common law country (+), Platform age (+)

Usman et al., 2019	Information asymmetry	Role of media, Experience	Signals	Role of media (+, both video and images), Past CF success (+), Duration (-), Updates (+), Comments (+), Number of URL links shared (+)
Vismara, 2019	Sustainable development; Signal interpretation	Firm characteristics, Human capital, Campaign characteristics, Business characteristics	Signals and different interpretations (characteristics of the receiver)	Sustainability (+/-, but attracts more crowd investors; not professionals), Team size (+, but not for professionals), Entrepreneur experience (+/-), Target capital (+, but for investors only and not for success), Equity offered (-), Serial entrepreneur (+/-), Tax incentives (+/-),
De Crescenzo et al., 2020	Contingency factors of ECF	Firm characteristics, Campaign characteristics	Signals and Contingency	Firm age (-), Industry sector (+), Team size (+), Gender (+, failure if not female), Reward (-, they prefer financial returns), Pictures (+)
Kleinert et al., 2020	Entrepreneurial finance, Signaling	Prior funding, Human capital, Social capital, Firm stage, Firm characteristics	Signals with moderation effects	Prior funding (+): CF (+), VC (+, but only for no. Investors), BA (+, but only for no. investors), Grant (+, but not for no. investors). Market access (+, but not on number of investors), Entrepreneur education (+), Technology (-, but only for number of investors), Exit plan (+), Funding goal (+, but only for number of investors), Multiple investor types (+), Revenues/sales (+), moderation effects of social capital (+, Non-Executive Directors), moderation effects of seed stage (+)
Ralcheva and Roosenboom, 2020	Entrepreneurial finance and ECF	Campaign characteristics, Firm characteristics, Intellectual capital, Human capital	Signals	Equity offered (-), Funding goal (+/-), External financing (+), Accelerator attendance (+), Firm age (-), Team size (+), Entrepreneur age (-), Prior ECF funding (Follow-on campaign) (+), Intellectual property rights and patents (+/-)
Xiao, 2020	Trust theory and early-stage financing	Trust	Signals, Trust building, Platform intermediation	

Lim and Busenitz, 2020	Signaling and CF; Human capital characteristics	Human Capital, Team characteristics (moderation effect)	Signals	Human capital (+): university education(+), management experience in SMEs (+), management experience in large companies (+/-), startup experience of previous ventures (+), startup experience of ongoing ventures (-). Team characteristics (+): team size (+,dummy: lone founder or team-based). Control: sales (-), Intellectual capital(+,number of patents(+), proportion of MBAs (+)), funding target (+), team board/employee size (+/-), location (+/-), prior CF funding (+/-,dummy).
Shafi, 2021	ECF and professional investors' criteria	Human capital (team characteristics), Firm characteristics (business), Financial information and metrics	Evaluability heuristics	Management: management rating (+), Commitment (+), Experience (+/-), Skills (+/-). Business: business rating (+), Market rating (+/-), Product rating (+/-), Competition rating (+/-). Financials (+/-). Control: Prior CF success (+), Equity offered (-), High-tech (+/-), London (+/-), Funding target (+/-), Firm age (+/-), Tax relief (+/-).
Andrieu et al., 2021	ECF and female entrepreneurship, homophily theory	Gender	Female risk aversion and homophily theory	Gender (-); Control: Entrepreneur characteristics: (+/-,PhD level ( ), Hi-Tech Experience (+/-), Ethnicity (+/-)), firm maturity (+/-), geographical location (+/-) funding goal (-), date (+/-), platform (+/-).
Dority et al., 2021	ECF determinants, signaling, information asymmetry and information overload	Pitch descriptions: textual analysis in CF and information overload	Signals; Tone and readability of descriptions, information overload (Less is more)	Readability: Information quantity (Word count (+) word count^2(-)), information quality (SMOG(+), SMOG^2(-)); Tone (Information attitude (+), information attitude^2(-)). Control: (gender (+/-), funding goal (-), prior seed financing (+), VIX volatility level(-)).
Meoli and Vismara, 2021	Signaling, digital finance, social finance, information manipulation	Withdrawal rights	Signals; Information manipulation	Platform-member investment (-), Platform-member withdrawal (+). Control: funding target (-), team size (+/-), sales (+), equity offered (-).
Vrontis et al., 2021b	Knowledge sharing, singaling	Intellectual capital, Social Capital, Platform characteristics, Campaign characteristics	Knowledge sharing and information dissemination	Platform Information HUB (+), Number of campaigns on platform (+/-), Intellectual capital (+), Geographical distance(+/-), Number of shareholders (+), Team size (+/-), Reward (+), Equity retention (+/-), Campaign success (+).

Coakley et al., 2022	Signaling	Team characteristics, Human capital	Signals, certification effect	Team size (+, lone founder (-)), Human Capital (+, Tenure heterogeneity (+), Age heterogeneity (+), Advanced degrees(+)) .Controls: (Premoney (+/-), Firm maturity (+, startup dummy(-)), location (+/-), equity offered (+/-), diversification (-), funding target (+/-), number of investors (+))

For this reason, the readability of a pitch description plays a crucial role both in terms of information quantity and quality (Dority et al., 2021), following a non-linear effect, but rather quadratic ("Less is more" effect, Dority et al., 2021).

Nevertheless, elements of sustainable development are not critical to reaching the financial goal, but they can positively affect the capital raised (Motylska-Kuzma, 2018) or the number of crowd-investors but not professionals (Vismara, 2019). On the contrary, we note that high-tech industries, such as the business area, seem not to be relevant for investment decisions (Barbi and Mattioli, 2019), or even give more uncertainty (Ahlers et al., 2015; Piva and Rossi-Lamastra, 2018).

Team characteristics and human capital

A considerable part of information that can be disseminated easily during the web-based campaign is the human capital hired in the venture, in its four main dimensions: team size and composition, gender, education and experience of the entrepreneurial team.

The management composition of a venture is an easily observable factor that can affect the investors' willingness-to-invest and thus the outcome of an ECF campaign. Many authors have studied the impact of the team size (number of entrepreneurs or directors of the board), and its education (human capital). On this subject, literature is unanimous in affirming that an additional number of team members of a venture is positively related to an increasing probability of successfully raising crowd-financing (Li et al., 2016; Vismara, 2016; De Crescenzo et al., 2020; Ralcheva and Roosenboom, 2020; Lim and Busenitz, 2020; Coakley et al., 2022), although in some cases the effect is weak/not significant (Vulkan et al., 2016; Piva and Rossi-Lamastra, 2018) or is able to attract only crowd-investors and not professional investors (Vismara, 2019). Larger teams are perceived by the investors as more capable of alleviating the execution risk of a business strategy and proving the viability of the business model (Mamonov and Malaga, 2019), especially if compared to lone-founder-based teams (Lim and Busenitz, 2020; Coakley et al., 2022).

In relation to team size, other studies separated the effect into ventures led by a single entrepreneur and ventures led by a larger team and found that lone founders are less likely to be funded than team-based ventures (Mamonov and Malaga, 2018, Mamonov and Malaga, 2019; Lim and Busenitz, 2020).

The gender variable, namely a dummy variable of the female representation on the entrepreneurial team, has an uncertain effect on the likelihood of being financed. Vismara (2016) found that female entrepreneurs have the same ability as male entrepreneurs in attracting investors (negative but non-significant relationship), but they raise less capital. Similarly, Piva and Rossi-Lamastra (2018) and Malaga et al. (2018) found a negative but non-significant effect. Barbi and Mattioli (2019), contrarily to Vismara (2016) found a positive and significant effect on the number of investors, but non-significant for the amount raised. However, the authors go further than previous literature and split the gender effect into two variables: a dummy variable on the presence of women and the number of female entrepreneurs within the team. The latter variable shows a positive and significant relationship for both number of investors attracted, and amount of capital raised.

More recently, De Crescenzo et al. (2020) found a positive impact on success of ECF campaigns, showing that the representation of women in new ventures is generally valued, but most importantly found that failure to ensure female representation is associated with failure of campaigns.

Although traditional literature has addressed the gender effect mainly as a control variable, Malaga et al. (2018) investigated it as the main determinant of ECF success via an exploratory analysis. They found that female representation generally does not procure success in ECF (except for the real estate industry), but also that women-owned ventures are under-represented showing that perhaps ECF and digital platforms do not facilitate female entrepreneurship. A more recent study of Andrieu et al., 2021 is in line with these results.

Only more recent research has focused on the education and experience dimensions of human capital. Many authors discovered a positive relationship between the education of team members, which can be deduced from the possession of degrees, MBAs, skills, etc., and the success of a campaign (Piva and Rossi-Lamastra, 2018; Barbi and Mattioli, 2019; Nitani et al., 2019; Kleinert et al., 2020; Lim and Busenitz, 2020; Shafi, 2021; Coakley et al., 2022). In particular business education seems to have a significant effect, while other types of education are irrelevant (Piva and Rossi-Lamastra, 2018). An alternative way to evaluate human capital is suggested by Shafi (2021) who assigned a rating based on skills deduced from bios of entrepreneurs, rather than using dummy variables for education.

Investors, in fact, tend to be attracted by well-educated founders, especially in business, in the attempt to reduce investment risks (Nitani et al., 2019; Kleinert et al., 2020) and to give more credit to the founders' education level, rather than to their experience (Piva and Rossi-Lamastra, 2018), showing that innovativeness is particularly appreciated by crowd-investors.

The mere entrepreneurial experience, in fact, does not seem to significantly affect the success of a campaign (Mamonov and Malaga, 2018; Vismara, 2019; Shafi, 2021), unless it regards professional business (Barbi and Mattioli, 2019; Lim and Busenitz, 2020). Different results are found by Mamonov and Malaga (2019), Nitani et al. (2019) and Cumming, Meoli, et al. (2019), who claim that serial entrepreneurs with prior experience are more likely to raise funding, especially if gained in SMEs or previous startups (Lim and Busenitz, 2020).

Other studies have focused on crowdfunding experience and claim that investors see it as a sign of good quality of a project that can positively and significantly affect success (Usman et al., 2019; Kleinert et al., 2020; Ralcheva and Roosenboom, 2020). Entrepreneurs' age is not necessarily related to experience and Ralcheva and Roosenboom (2020) also found that it has a negative impact on the likelihood of success.

Recently, Coakley et al. (2022) focused on the heterogeneity within a venture team and found that differences in tenure and age are embraced by investors.

Social capital and social media network

Besides the human capital hired in a venture, literature suggests the importance of social capital, which refers to entrepreneur interconnections and their relational capital. Early ECF literature investigated this aspect by looking at the number of non-executive board members, who are industry veterans that act as mentors to new ventures, as a proxy for alliances, but these authors found no significant effect (Ahlers et al., 2015). Differently, Lukkarinen et al. (2016) prove the importance of entrepreneur network in obtaining private funding in an early hidden phase, as a signal to crowd-investors before launching the campaign.

More recently, social media and digital instruments are recognized as an essential part of social capital and are crucial in a funding scheme that is based upon a digital environment (Cumming, Deloof, et al., 2019), since they provide not only wider publicity of the campaign through the sharing of pitch videos and projects, but also benefits in the form of information sharing, access to information, timing and referrals (Wald et al., 2019). Hence, social capital and the interconnections of entrepreneurs, such as their openness to social networks, have been found to hold a strong positive influence on investment decisions in that they provide an opportunity to lessen information asymmetries and validate less credible information (Nitani et al., 2019). Social media network, especially the connections on LinkedIn, is considered indeed a good predictor for the success of a campaign (Vismara, 2016; Piva and Rossi-Lamastra, 2018; Nitani et al., 2019). Nevertheless, a recent study by Kleinert et al. (2020) addressed social capital as a moderation effect for signaling and mentioned the measure suggested by Ahlers et al. (2015) but confirmed controversial effects and claimed that perhaps the number of non-executive directors is an endogenous measure, implying a non-random distribution.

Digital media usage and interactions

However, the mere presence on social media cannot entirely explain the effect of social (media) capital on ECF outcome. Hence, some authors shifted their attention to popularity in media, newspapers and TV (Barbi and Mattioli, 2019). In this sense, literature is unanimous in claiming that ECF campaigns benefit from entrepreneurial interactions with the crowd, such as posting updates on the project or on the progress of the campaign, discussions and comments (Li et al., 2016; Lukkarinen et al., 2016; Kleinert and Volkmann, 2019b), since they mitigate information asymmetry and induce positive attitudes (Li et al., 2016).

Posting updates regularly positively affects the outcome of the campaign (Li et al., 2016; Block et al., 2018), but not all kinds of topics appear to be effective. In fact, some recent studies shifted the focus from the quantity of updates to the quality and found that updates concerning business development and new funding, and updates about campaign developments and cooperation projects have positive effects on crowd participation and are highly valued by investors (Block et al., 2018). On the contrary, updates concerning team developments, business models, product development and campaign promotions are meaningless for crowd-participation, since information on these topics basically does not change during a campaign and investors expect to receive it usually at the beginning (Block et al., 2018). Moreover, the frequency of updates provided by entrepreneurs should be regular and not abundant, otherwise investors perceive them as “cheap talk” and this could cause a loss of credibility (Block et al., 2018). Similarly, one year later Kleinert and Volkmann (2019b) investigated discussion topics and claimed that a significant effect can be found in topics regarding: market risk, financial snapshot, investment return expectations and shareholders' rights.

Moreover, it is not negligible that digital media offer entrepreneurs the opportunity to present pitch videos, pictures and detailed descriptions of the business idea and some authors addressed the effect of their presence and quality. ECF outcome benefits from pitch videos, representing a visual introduction of the project and/or of the entrepreneur (Li et al., 2016; Mamonov and Malaga, 2019; Usman et al., 2019; De Crescenzo et al., 2020). Similarly, when a project is presented using meaningful pictures, it has higher chances of success (Usman et al., 2019), since pictures and videos are considered as proxies in communicating the good quality of a project to investors and promoting the campaign (De Crescenzo et al., 2020). However, the presence of the entrepreneur her/himself in the videos seems to have no significant effect on the likelihood of success of a campaign (Mamonov and Malaga, 2019). The length of project description appears to be beneficially acclaimed by crowd-investors as well (Li et al., 2016).

Investor characteristics

On the demand side of the ECF, the presence of professional investors is a good quality signal and attracts crowd-investors. On one hand, crowd-investors presume that professional investors are better informed. Following the information cascade theory, they mimic the same decision (Mamonov and Malaga, 2018; Mamonov and Malaga, 2019; Kleinert et al., 2020), resulting in herd behavior.

On the other hand, recently Vismara (2019) treated the professional investor effect not as a determinant of ECF success (explanatory variable), but rather as an indicator of success (dependent variable) and found that their investing preferences slightly differ from the crowd.

Note that this approach is not new, as Vulkan et al. (2016) are the pioneers in addressing the number of investors as an explanatory variable rather than a dependent variable and they found that investors currently involved in the campaign, the capital raised in the first week and their largest investment can positively affect the outcome by inducing herding behavior. However, excessively high early investments can be perceived as a collusion risk and thus as a negative signal (Li et al., 2016).

An interesting recent study from Meoli and Vismara (2021) treated the investment bids made by platform-members as a potential sign of information manipulation, as they likely withdraw the bid right before the conclusion. Thus, their intervention is not crucial for successfully concluding the campaign, but rather to drive the crowd through signals (Meoli and Vismara, 2021).

Campaign characteristics

Several parameters of the crowdfunding campaign per-se have been investigated in order to understand their impact on investors' willingness-to-invest: minimum investment, funding goal, duration of the campaign, presence of professional investors, taxation benefits and presence of exit strategies.

The minimum investment required represents the price that an investor must pay to obtain a share. Although it is not extensively studied in the literature, Lukkarinen et al. (2016) found a negative strong relationship with the success of a campaign, a sign that higher prices seem to discourage crowd-investors to take risks. The funding goal, i.e., the minimum target amount of capital to be raised to reach the goal, is controversial in explaining ECF outcome. On one hand a higher target seems to discourage investors and has a negative effect on success (Vulkan et al., 2016; Piva and Rossi-Lamastra, 2018; Ralcheva and Roosenboom, 2020); on the other hand, a higher maximum funding goal signals good quality of the project and entrepreneur self-confidence, in that it does not affect the relative capacity of the campaigns to raise funds but the number of investors involved, as a size-effect (Lukkarinen et al., 2016; Vismara, 2016; Vismara, 2019).

Longer campaign duration represents a negative signal to the crowd and negatively affects the likelihood of raising funds (Lukkarinen et al., 2016; Vismara, 2016; Usman et al., 2019).

Declaring an exit strategy option is again controversial in explaining ECF outcome. Early literature found that it is not an effective signal since it is perceived as "cheap talk" (Ahlers et al., 2015), while recent literature found that it attracts more investors and fosters the probability of success (Kleinert et al., 2020), by reducing the liquidity risk of investors. However, some authors disentangled the effect of different exit strategies and found that the declared intention of entrepreneurs in having an IPO exit might positively affect campaign outcome (Nitani et al., 2019), but the declared exit intention after five years from the start of the campaign or through an M&A seems to attract fewer investors (Vismara, 2016; Nitani et al., 2019).

Some literature addressed the pledge of rewards in addition to shares and found a negative effect on the outcome, since investors seem to rather prefer financial returns from an ECF investment (Barbi and Mattioli, 2019; De Crescenzo et al., 2020). Nevertheless, a more recent study from Vrontis et al. (2020) went in the opposite direction and found a positive impact on success.

Role of platforms and trust

It is important to outline that the ECF platforms can influence the likelihood of raising funds through their key role of intermediaries and syndicates. Löher (2017), in a qualitative study, states that managers of platforms need to select the best available ventures to be launched on their website; then, the digital environment should create a favorable setting for achieving the funding goals of campaigns; finally, platform managers should work on communication to reduce information asymmetries and enable investors, after adequate advertising, to invest consciously. Hence, efficient platforms reduce search and due diligence costs, alleviate information asymmetries, transaction risks, allocate capital more efficiently, enhance economic growth by reducing market failures and act as syndicates for investors (Agrawal et al., 2016; Löher, 2017; Xiao, 2019)

An article from Xiao (2019) assessed via qualitative interviews the importance of building interpersonal trust between entrepreneurs and investors to ease investment decisions of unsophisticated investors who have limited resources and lack of expertise to evaluate investment opportunities. In this, the ECF platforms appear strategic to facilitate the process of building relational trust.

A very recent study from Vrontis et al. (2020) asserts the crucial role of platforms as an information hub to disseminate information and share knowledge among investors, with a focus on Twitter.

Determinants of failure

We need to comment that even if the extraction queries were neutral in terms of outcome, when the words “success” and “failure” were included, most existing literature focused on what can be empirically related to a successful fundraising campaign. On the one hand, predicting signals for failure could be implicitly deduced by the negative version (or absence) of these determinants. On the other hand, research has only recently addressed explicit determinants of failure (De Crescenzo et al., 2020) claiming that success and failure are not symmetric and cannot be considered opposites. Their findings show that failure is more likely to occur for ventures that do not have female entrepreneurs, operate in traditional sectors (and not high-tech), are no longer at the early stages, publish few pictures and pledge rewards in addition to shares.

2.7 Results from the bibliometric analysis

In parallel a bibliometric analysis was conducted in order to provide a more complete picture of the literature investigated. The analysis was conducted via the Bibliometrix tool with the R-software.

Sources

It is interesting to begin the source examination from the Bradford's law (Bradford, 1934). It is an estimate that identifies the core of scientific production for a certain topic according to the citation count of the sources and their number of articles published on the same topic, by sorting the sources into three main groups. In this sample, the core group is represented by three journals: Small Business Economics, Venture Capital and Sustainability. They respectively published six, five and two articles on the topic (Figure 2.7). However, if we look at the in-sample citation count from the reference list, the rankings are slightly different, with the Journal of Business Venturing at the top (162), followed by the Entrepreneurship Theory and Practice (126), Small Business Economics (96) and Venture Capital (67). With regards to their impact for their articles on this topic, Small Business Economics has the lead with a H-index of 3, a G-index of 6 and a Total Citation count of 204, and is followed by Venture Capital follows (h-index=2, g-index=4 and Total Citation=19) and Sustainability (H-index=1, G-index=2 and Total Citation=4). The Journal of Business Venturing falls back with a H-index and a G-index of 1 and a Total Citation of 19. Looking at the source growth, Small Business Economics is the journal with the higher growth rate for cumulate occurrences in recent years.

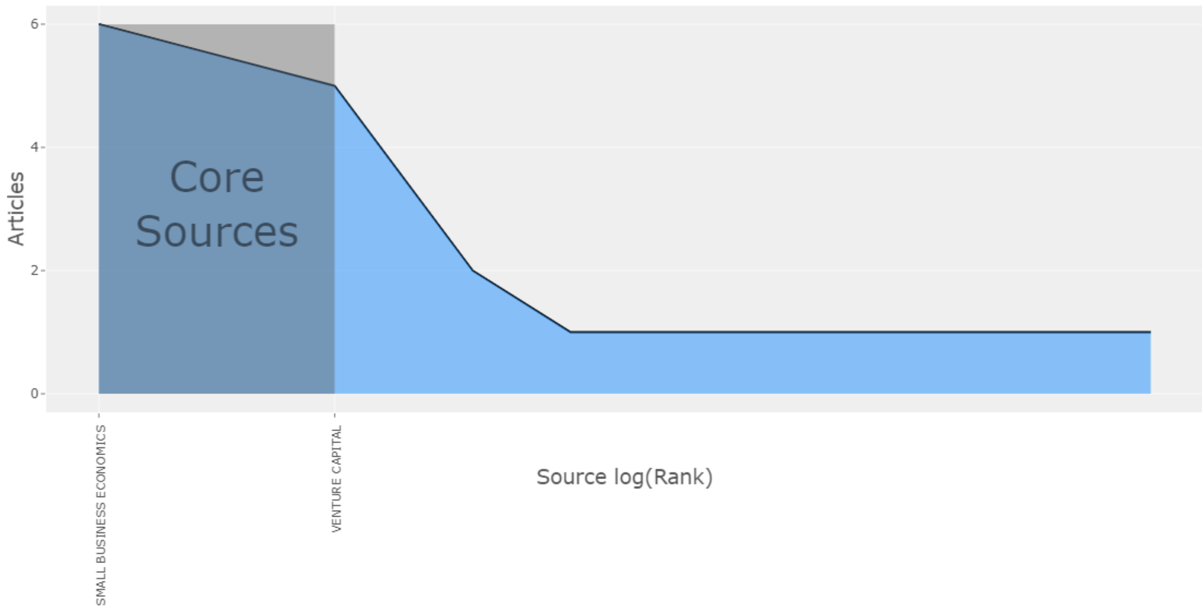


Figure 2.7: Bradford's law

Authors

In table 2.7 are presented the most influential authors in this sample. Two parameters are considered: the productivity (left side) and the fractionalized frequency distribution of articles per author. In particular, Vismara S. is the most relevant author concerning the research on successful factors in equity crowdfunding campaigns with four articles published and a fractionalized frequency distribution of 2.17 articles. However, in terms

Authors	**Articles**	**Articles Fractionalized**
Vismara S	4	2.17
Malaga R	4	1.83
Mamonov S	4	1.83
Lher J	2	1.33
Kleinert S	2	0.83
Volkmann C	2	0.83
Meoli M	2	0.67
Cumming D	2	0.58
Ahlers GKC	1	0.25
Badulescu D	1	0.20

Table 2.7: Articles per author

of citation count, the most influential authors appear to be Cumming D., Ahlers G.K.C. and Günther C. with their paper "Signaling in equity crowdfunding" (Ahlers et al., 2015) that has been cited 381 times (see table 2.8). In spite of this, Vismara S. boasts the second most cited paper among this sample (Vismara, 2016).

Author	Year	Title	Tot. citations	Auth. citation
Cumming D	2015	Signaling in equity crowdfunding	381	63.5
Ahlers GKC	2015	Signaling in equity crowdfunding	381	63.5
Günther C	2015	Signaling in equity crowdfunding	381	63.5
Vismara S	2016	Equity retention and social network theory in equity crowdfunding	134	26.8
Block J	2018	Which updates during an equity crowdfunding campaign increase crowd participation?	53	17.667
Vismara S	2018	Does success bring success? The post-offering lives of equity-crowdfunded firms	35	11.667
Lher J	2017	The interaction of equity crowdfunding platforms and ventures: an analysis of the preselection process	14	3.5
Di Pietro F	2018	Crowd equity investors: an underutilized asset for open innovation in startups	11	3.667
Malaga R	2018	Success factors in title III equity crowdfunding in the united states	9	3
Mamonov S	2018	Success factors in title III equity crowdfunding in the united states	9	3

Table 2.8: Citations per article

Affiliations

Figure 2.8 represents the scientific production on the topic per country. The darker the colour, the more intense is the productivity. At a glance, the most productive countries for this topic are Italy, Germany and United States. Table 2.9 shows the number of articles published in each country, dividing it into "single country collaboration" (SCP) and "multiple country collaboration" (MCP), which specify whether an article was originated in collaboration with other countries or not. Italy has the highest productivity and the highest frequency of multiple country collaboration, showing a good interrelation among different affiliations.

References analysis

With regard to the references mentioned in the sample, table 2.10 shows the most cited articles within the sample (local citations) and outside (global citations). The documents

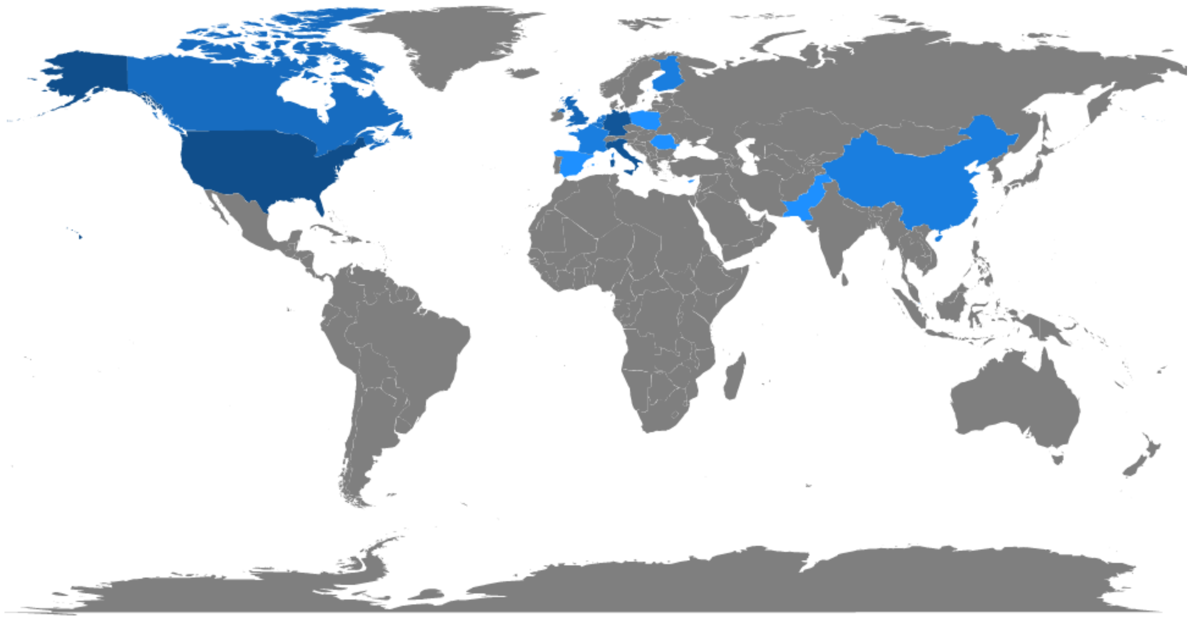


Figure 2.8: Country scientific production

Country	Articles	Frequency	SCP	MCP	MCP Ratio
Italy	7	0.3684	4	3	0.429
Germany	3	0.1579	2	1	0.333
Usa	3	0.1579	3	0	0
Canada	1	0.0526	0	1	1
China	1	0.0526	1	0	0
Finland	1	0.0526	0	1	1
France	1	0.0526	0	1	1
Netherlands	1	0.0526	1	0	0
Portugal	1	0.0526	1	0	0

Table 2.9: Articles production per country

of Ahlers et al. (2015) and Vismara (2016) come out to be once more the most influential studies both locally and globally. Figure 2.9 represents the references spectroscopy per publication year, thus reflecting the trend in citation. The plain graph stands for the number of references per year, whether the red line for the difference of median along adjacent years. The core of the references is situated between the years 2013-2018, with a peak on the year 2015, proofing the novelty of the topic. It is important to notice that the decreasing trend of recent years should not be interpreted as a downfall, but rather as an inevitable lack of data about the most recent articles in progress or not published yet.

Document	Local citations	Global citations
Ahlers et al., 2015	26	381
Vismara, 2016	19	134
Lukkarinen et al., 2016	14	71
Vulkan et al., 2016	11	62
Piva et al., 2018	4	16
Lher et al., 2017	1	14
Block et al., 2018	1	53
Signori et al., 2018	0	35
Walthoff-borm et al., 2018	0	19

Table 2.10: Reference citations

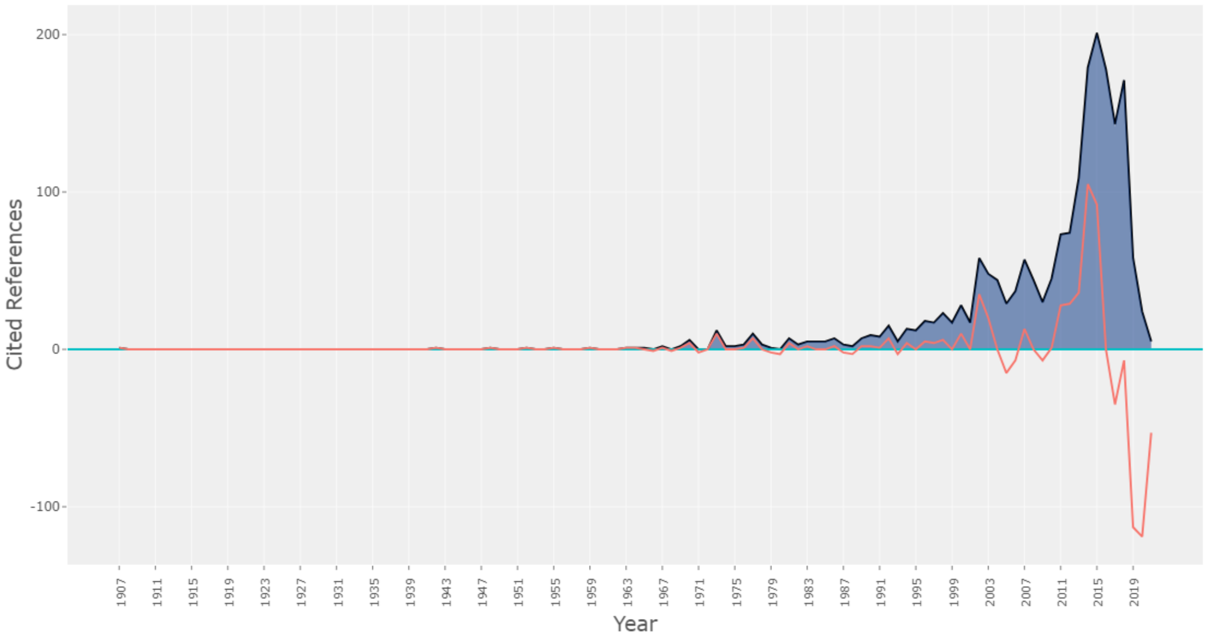


Figure 2.9: Reference publication year spectroscopy

Keywords

An interesting analysis might be done on the keywords present in each paper. Indeed, the keywords selected and put on evidence by the authors give a short summary of the themes that will be covered throughout the article and in a nutshell give the big picture of the study. Figure 2.10a condenses in a word-cloud the most recurrent keywords selected by the authors, sorting by the log of the occurrence frequency: the higher the font, the greater the log-frequency. Not surprisingly, the most cited word is "crowdfunding", together with "campaign success" and "equity", which were indeed the keyword-filters for the generation of the sample. However, it is interesting to notice that the following covered topics are "alternative finance", "information asymmetry", "signaling", "risk capital", "corporate governance" and "agency risk". They define the matter on which research about equity crowdfunding success has focused since its establishment. In other words, since the beginning equity crowdfunding has been assimilated to a stock market investment for certain aspects and thus classical theories from traditional economics and finance settings have been applied to this new phenomenon with the aim to explain its success and investors' decision.

Keywords are generally elicited by the authors themselves and although they try to provide a complete picture of the topics covered, some other themes might be left out. Hence, Thomson Reuters editorial selects and adds a new set of keywords (keywords plus), which are considered to be relevant to the document. Figure 2.10b shows how the word-cloud changes if the log-frequency of the keywords plus is examined. The word "crowdfunding" has still a central role, but the most addressed word in this case is "investments", showing the different nature and perception of the equity crowdfunding phenomenon compared to other types of crowdfunding. Considering the subsequent importance of the word "finance", it comes naturally the association between this method of alternative financing and the initial public offering on stock markets.

Another important concept that comes out from this analysis is the digital approach of this financing scheme ("Digital storage" and "fintech"), which comes out frequently also in the definitions of equity crowdfunding present in literature. Additionally, Thomson Reuters' keyword plus highlight the explanatory nature of these studies by adding the words "Driving factors", which combine the articles for their investigation of the drivers of success of the campaigns.

To conclude this section, it is remarkable that in recent years is taking root the concept of "entrepreneurial finance", which indeed makes the equity crowdfunding phenomenon a rational and thoughtful strategy in the natural growth path of a new venture, rather than an occasional mean of raising extra money (Figure 2.11).

Network

An interesting conclusive deduction from the bibliometric analysis is the network analysis on the top authors of this topics. In particular, this analysis gives the co-citation network between the authors in and outside the sample (Figure 2.12). The clustering algorithm implemented is based on Louvain and set a threshold of 5 minimum edges per each

(a) Keywords (b) Keywords plus

Figure 2.10: Keywords

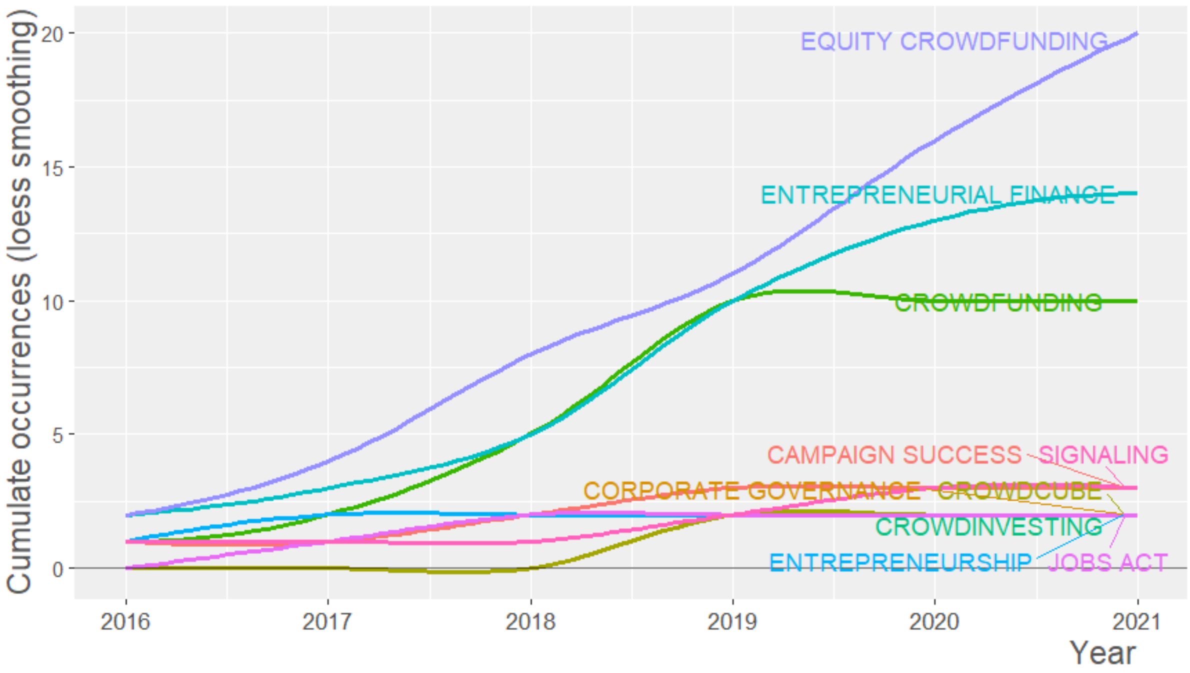


Figure 2.11: Word growth (cumulate)

node. Three main clusters are identifiable and are highlighted in red, green and dark blue. The first one (green) includes Mollick, Agrawal and Belleflamme. The pivotal nodes are Mollick and Agrawal with a betweenness centrality of about 123 and 50. The second cluster (blue) is hinged on Ahlers, Vismara and Cumming who have respectively a betweenness centrality of 261, 79 and 45. The third cluster (red) rotates around Colombo, who has a betweenness centrality of 97.

2.8 Discussions

Running an ECF campaign always raises a situation of asymmetric information, where the two financially involved parties (entrepreneurs and investors) do not possess similar

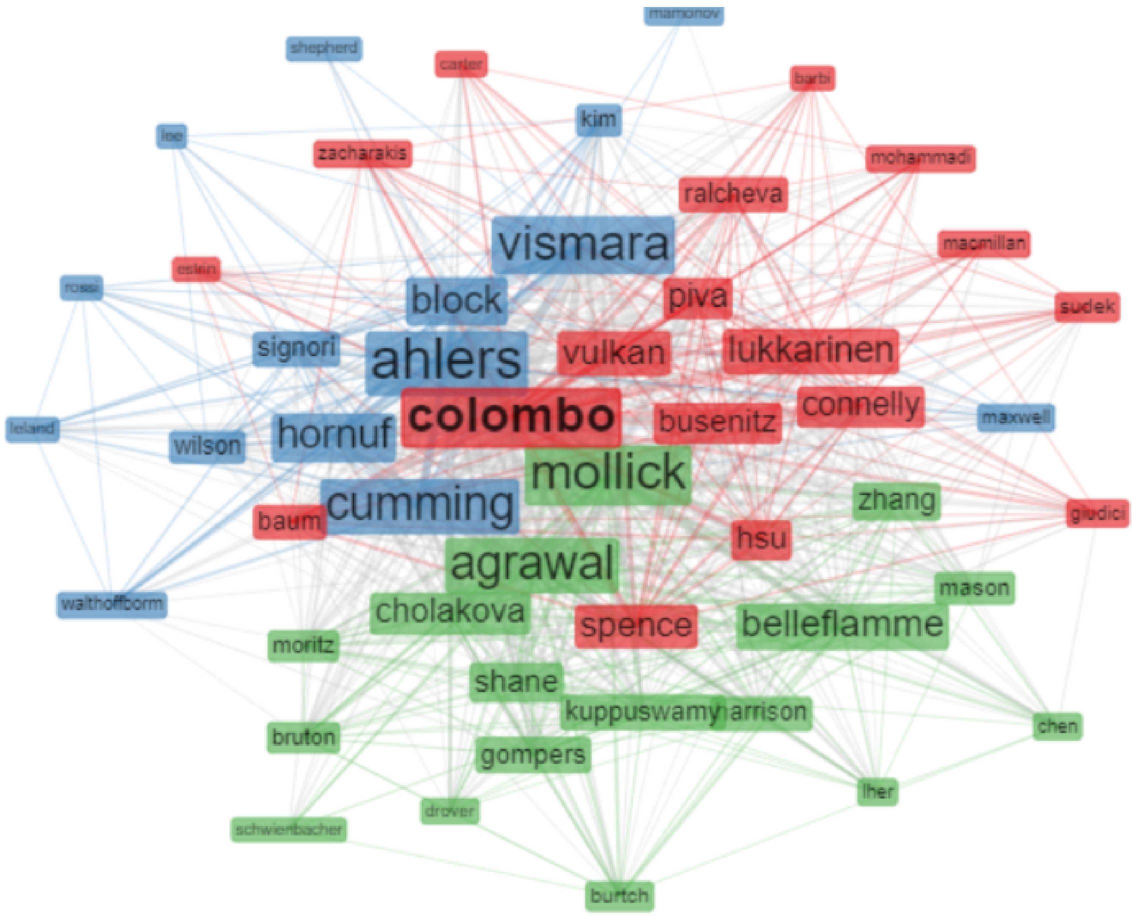


Figure 2.12: Co-citation network

sets of information, especially for new ventures with no historical data available. This discrepancy must be overcome by launching signals about the quality of the project and its outlook. Hence, signaling strategies are the key mechanism, as emerges from the thematic analysis, and the present study sheds lights on which signals are decisive in improving an ECF campaign outcome, taking into consideration various disciplines which follow different but complementary perspectives.

From the existing literature, positions are somehow contradictory. On the one hand, according to Nitani et al. (2019) crowd-investors capture signals and assess rationally the risk-return characteristics of projects. On the other hand, Vismara (2019) claims that interpretation of signals is different according to the characteristics of the receiver. Kleinert et al. (2020) suggest that signals are moderated by other variables. Sometimes signals can induce herd behaviors and amplify their effect (Vulkan et al., 2016; Nitani et al., 2019; Kleinert and Volkmann, 2019b).

Overall, existing research lacks a systematic analysis of papers that bring arguments in favor of (or against) those signals that can be used to predict the outcome (positive or negative) of an ECF campaign. This gap motivates our paper that investigates what in the literature has been found to lessen informational asymmetries, to reduce adverse selection cost and increase the willingness to invest, expressed by a highly heterogeneous population of investors.

The thematic analysis offered in the previous section can be interpreted through the lens of a traditional paradigm used to deal with information asymmetries between lenders and debtors, and that generally considers hard and soft information (among others, see Liberti and Petersen, 2019). So, the outcome (success) of an ECF campaign is related to a hard information set, such as firm characteristics, development stage, location of headquarters, pre-money valuation, client portfolio, attendance of acceleration programs, intellectual capital and patents, business characteristics and project description. Nevertheless, soft information variables are even more strongly relevant, such as team characteristics and human capital, social capital and social media network, catalyzed by digital media that facilitate also personal interactions between entrepreneurs and investors.

Also, existing studies underline the importance of investor characteristics, campaign characteristics, and the fundamental role of managers of ECF platforms in building trust between entrepreneurs and investors.

As a result, entrepreneurs should be aware of the potential impact of these signals and adopt coherent signaling strategies in order to stand out and reveal their true quality, always keeping in mind the variety/complexity of attitudes and behaviors of investors who are going to receive their signals. Moreover, entrepreneurs should also define the optimal parameters (i.e. duration, target, minimum investment, etc.) of their campaign in concert with ECF platforms to encourage/not discourage crowd participation.

Some factors are clearly intrinsic to their project or characteristics and cannot be modified in a short time or during an ECF campaign. However, entrepreneurs could still aim at presenting their unique quality traits without losing credibility and stumbling on "cheap talks", and at building durable relationships with the crowd by taking advantage of social media and digital instruments. In particular, the latter are viable instruments to acquire consensus. The presence of social media, and most importantly the frequency and quality of their interaction, proves to have an effective impact on attracting the interest of investors.

Additionally, people who decide to invest in ECF might not be involved in financial measures, or perhaps lack the abilities to understand them, but rather look at different sources of information and be reluctant to invest in a project that is not easily comprehensible or effectively presented.

Research agenda

Research demonstrates a need for analyzing a broader range of signals, as well as a need for extending both numerically and geographically the sampling of cases of ECF campaigns, to capture cultural differences, since the digital nature of ECF obliges to move towards innovative and unconventional explanatory variables. As an example, text descriptions, pictures and pitch videos have a large impact on a crowd's willingness-to-finance and cannot be overlooked. Moreover, current research seems not to converge on the choice of a target variable for defining success/failure. Future research should focus on a comparable and relative measure rather than on absolute values.

More research should address the different dimensions of an ECF process and their determinants: (i) the phase in which an entrepreneur looking for financing decides to opt for ECF; (ii) the pre-screening phase in which a platform assesses the quality of a proposed project; (iii) the post-offering lives of financed ventures. In particular, few authors have tried to identify the successful characteristics of a campaign that also lead to post-offering success, i.e. to generate long-term growth and avoid subsequent failure, since they may not coincide.

Importantly, our SLR revealed that ECF literature seems to lack studies on determinants of failure of campaigns, thus more research is encouraged in this field.

A different perspective of analysis would be to investigate investors' willingness-to-invest via different methodologies, i.e. choice models that could experimentally assess their investment behavior and choice preferences. Additionally, dynamic studies via panel datasets are not common in literature, but they could uncover deeper effects that might not emerge from static (i.e. analysis on the outcome) works. Despite the growing interest of economic research in artificial intelligence and machine learning models, recent literature surprisingly lacks studies focused on the adoption of these techniques, which could provide different and interesting results compared to traditional methods.

Moreover, although official and reliable databases of ECF campaigns are sporadic, re-

Theme	***Further research and perspectives***
Behavior	Investors' perspective- Comparisons between behavior in stock market and behavior in equity crowdfunding environment. -Elicit investors' preferences through models of investment choice behavior. Entrepreneurs' perspective- New communication skills in the Fintech environment.
Business sector	Entrepreneurs' perspective- From declaration to facts: effectiveness of the declared business sector compared to the one emerging from description. -New ways of classification. -Which sectors attract more funding?
Communication/video	Entrepreneurs' perspective- How to make an effective and convincing pitch video?
Determinants of failure	Entrepreneurs' perspective- focus on the determinants of failure of a campaign, as well as on the post-offering phase.
Digital media	Entrepreneurs' perspective- Exploiting new technologies and media to promote business and ask for financings. Investors' perspective- How does investment risk perception change with new technologies?
Entrepreneurship	Entrepreneurs' perspective- Changing attitude in asking for trust over the Internet.
Financial Intermediation	Platforms' perspective- Application of traditional theories about financial intermediation to ECF platforms. Role of ECF platforms as intermediaries.
Geography	Investors' perspective- Cross-country comparison of platforms all over the world to catch cultural investment differences.
Information asymmetry	Investors' perspective- Coping with it in a less sophisticated environment of crowd. Entrepreneurs' perspective- Skills to deal with signaling techniques.
Looking for ECF	Entrepreneurs' perspective- explain what motivates a nascent entrepreneur to seek financing through ECF, and perceived positioning in the pecking order theory.
Marketing	Entrepreneurs' perspective- Self-branding and self-marketing in the digital era to promote business and attract funding.
Post-offering	Entrepreneurs' and investors' perspective- investigate results in terms of medium-term outcome of funded enterprises to uncover the predictors for post-offering success conditional to success in a campaign.
Pre-screening phase	Entrepreneurs' perspective- determinants of positively conclusion of the pre-screening phase. Platforms' perspective- competitive advantages that could be exploited by the digital platforms themselves via screening models of ECF projects.
Social media	Entrepreneurs' perspective- Which social media (and how) is more effective to promote business and funding campaigns? Studies on the efficacy of different types of social media, other than LinkedIn.
Text	Entrepreneurs' perspective: Do descriptions of the business affect financing decisions and persuade the crowd? What are the key aspects and how to make them effective?

Table 2.11: Research agenda

quiring researchers to access data directly from platforms, the process of their acquisition is still not explored in literature.

Finally, literature has surprisingly passed over an accurate analysis of the business sector, rather than the traditional dummy variable of high-tech industries, in which new ventures operate. We believe that it is an important determinant of ECF success and that it should be investigated in the perspective of comparing, perhaps with the aid of A.I. tools, the declared business sector and what comes out from project descriptions/pitch videos.

Table 2.11 offers a possible future agenda and presents some of the topics that appear worthy of investigation.

2.9 Conclusions

ECF is a recent and innovative way for new ventures to obtain alternative financing within a Fintech environment. It consists in raising capital from a wide range of investors by issuing ownership shares on a digital platform on the Internet. The digital nature of communication forces entrepreneurs to adapt their attitude and branding techniques in a dynamic era, finding new ways of promoting and financing their business ideas and products by means of novel technologies.

We argue that this is the direction in which ECF literature is moving in the near future, exploring new characteristics that could capture the crowd-investors' attention and drive their willingness-to-invest. ECF is addressed to a new type of investors, who might be less experienced with financial instruments and thus could look at different types of information, making it critical to provide easy-readable data. According to the "less-is-better effect" and to the "evaluability heuristic", unsophisticated investors may tend to evaluate fewer pieces of information and to attribute heavier weights to those which are easier to understand. As a result, entrepreneurs and platform managers have several lessons to learn.

2.9.1 Implications

We acknowledge that ECF is a valuable tool to support entrepreneurial finance and, as a result, ECF development could contribute to the spread of innovation and economic growth. This motivates the policy implications of this study, positioned within a large multidisciplinary framework, which proves that entrepreneurs, on the one hand, are experiencing changes of scenario and should adapt their behaviors to deal with the present digital era. Those willing to access to an alternative financing scheme, such as ECF, should be aware of the variety/complexity of skills requested to successfully manage digital campaigns as their attitude and communication skills can highly influence the outcome of their financing requests. On the other hand, platform managers could improve their knowledge of what persuades the crowd to invest, with more efficient project prescreening. Finally, implications for academics are advancements on knowledge of what causes the success/failure of ECF campaigns, within a wide spectrum of disciplines, as we offer a comprehensive review of key themes and dominant concepts involved in this issue.

Furthermore, we draw a possible agenda for further research, that should definitely exploit more pioneering and unconventional theories and research methods, such as those related to behavioral/phycological approaches as well as those related to Big Data and AI tools.

2.9.2 Limitations and future lines of research

As with other systematic literature reviews, we recognize the limitations of this study (e.g., Pascucci et al., 2018; Leonidou et al., 2020; Battisti et al., 2021). The first limitation is mainly due to the numerical paucity of the sample. Despite our effort to structurally collect an extensive set of relevant multidisciplinary literature on this topic within specific boundaries, the number of papers analyzed is still low. Moreover, additional literature could be identified based on different review protocols, even though that might not match our intended research question. Second, despite our effort to conduct the search among two largely comprehensive and multidisciplinary repositories, the coverage might not be exhaustive and other researchers might cover/analyse additional bibliographic sources. Third, this review includes only articles published in peer-reviewed academic journals and written in English. Other reviews might consider also books, conference proceedings ("grey literature", Leonidou et al., 2020), and also relevant articles in different languages. However, we believe that the articles examined in this review are representative of a body of literature addressed to answer our research question. Thus, the inclusion of all published studies might not be essential or realistic (Battisti et al., 2021).

Furthermore, we believe that these limitations leave room for future research opportunities and bolster the findings of our article which outline expected research trends and claim space and urgency for further future research according to the research agenda offered in this paper.

References for Chapter 2

Agrawal, A., Catalini, C., & Goldfarb, A. (2016). Are syndicates the killer app of equity crowdfunding? *California management review*, *58*(2), 111–124.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship theory and practice*, *39*(4), 955–980.

Andrieu, G., Le Pendeven, B., & Leboeuf, G. (2021). Equity crowdfunding success for female entrepreneurs: French evidence. *Economics Bulletin*, *41*(2).

Aria, M., & Cuccurullo, C. (2017). Bibliometrix: An r-tool for comprehensive science mapping analysis. *Journal of informetrics*, *11*(4), 959–975.

Barbi, M., & Mattioli, S. (2019). Human capital, investor trust, and equity crowdfunding. *Research in International Business and Finance*, *49*, 1–12.

Battisti, E., Graziano, E. A., Leonidou, E., Stylianou, I., & Pereira, V. (2021). International marketing studies in banking and finance: A comprehensive review and integrative framework. *International Marketing Review*.

Blaseg, D., Cumming, D., & Koetter, M. (2021). Equity crowdfunding: High-quality or low-quality entrepreneurs? *Entrepreneurship Theory and Practice*, *45*(3), 505–530.

Block, J., Hornuf, L., & Moritz, A. (2018). Which updates during an equity crowdfunding campaign increase crowd participation? *Small Business Economics*, *50*(1), 3–27.

Bradford, S. C. (1934). Sources of information on specific subjects. *Engineering*, *137*, 85–86.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, *3*(2), 77–101.

Briner, R. B., Denyer, D. et al. (2012). Systematic review and evidence synthesis as a practice and scholarship tool. *Handbook of evidence-based management: Companies, classrooms and research*, 112–129.

Briner, R. B., & Walshe, N. D. (2014). From passively received wisdom to actively constructed knowledge: Teaching systematic review skills as a foundation of evidence-based management. *Academy of Management Learning & Education*, *13*(3), 415–432.

Broadus, R. N. (1987). Toward a definition of "bibliometrics". *Scientometrics*, *12*(5), 373–379.

Coakley, J., Lazos, A., & Liñares-Zegarra, J. M. (2022). Equity crowdfunding founder teams: Campaign success and venture failure. *British Journal of Management*, *33*(1), 286–305.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, *37*(1), 39–67.

Cumming, D., Deloof, M., Manigart, S., & Wright, M. (2019). New directions in entrepreneurial finance. *Journal of Banking & Finance*, *100*, 252–260.

Cumming, D., Meoli, M., & Vismara, S. (2019). Investors' choices between cash and voting rights: Evidence from dual-class equity crowdfunding. *Research Policy*, *48*(8), 103740.

De Crescenzo, V., Ribeiro-Soriano, D. E., & Covin, J. G. (2020). Exploring the viability of equity crowdfunding as a fundraising instrument: A configurational analysis of contingency factors that lead to crowdfunding success and failure. *Journal of Business Research*, *115*, 348–356.

Diodato, V. P., & Gellatly, P. (2013). *Dictionary of bibliometrics*. Routledge.

Donaldson, G. (2000). *Corporate debt capacity: A study of corporate debt policy and the determination of corporate debt capacity*. Beard Books.

Dority, B., Borchers, S. J., & Hayes, S. K. (2021). Equity crowdfunding: Us title ii offerings using sentiment analysis. *Studies in Economics and Finance*.

Eckhardt, J. T., Shane, S., & Delmar, F. (2006). Multistage selection and the financing of new ventures. *Management Science*, *52*(2), 220–232.

Hsee, C. K. (1998). Less is better: When low-value options are valued more highly than high-value options. *Journal of Behavioral Decision Making*, *11*(2), 107–121.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), 305–360.

Kirby, E., & Worner, S. (2014). Crowd-funding: An infant industry growing fast. *IOSCO Research Department*, 1–62.

Kleinert, S., & Volkmann, C. (2019a). Equity crowdfunding and the role of investor discussion boards. *Venture Capital*, *21*(4), 327–352.

Kleinert, S., & Volkmann, C. (2019b). Equity crowdfunding and the role of investor discussion boards. *Venture Capital*, *21*(4), 327–352.

Kleinert, S., Volkmann, C., & Grünhagen, M. (2020). Third-party signals in equity crowdfunding: The role of prior financing. *Small Business Economics*, *54*(1), 341–365.

Leonidou, E., Christofi, M., Vrontis, D., & Thrassou, A. (2020). An integrative framework of stakeholder engagement for innovation management and entrepreneurship development. *Journal of Business Research*, *119*, 245–258.

Li, X., Tang, Y., Yang, N., Ren, R., Zheng, H., & Zhou, H. (2016). The value of information disclosure and lead investor in equity-based crowdfunding: An exploratory empirical study. *Nankai Business Review International*.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1–41.

Lim, J. Y.-K., & Busenitz, L. W. (2020). Evolving human capital of entrepreneurs in an equity crowdfunding era. *Journal of Small Business Management*, *58*(1), 106–129.

Löher, J. (2017). The interaction of equity crowdfunding platforms and ventures: An analysis of the preselection process. *Venture Capital*, *19*(1-2), 51–74.

Löher, J., Schneck, S., & Werner, A. (2018). A research note on entrepreneurs' financial commitment and crowdfunding success. *Venture Capital*, *20*(3), 309–322.

Lukkarinen, A., Teich, J. E., Wallenius, H., & Wallenius, J. (2016). Success drivers of online equity crowdfunding campaigns. *Decision Support Systems*, *87*, 26–38.

Malaga, R., Mamonov, S., & Rosenblum, J. (2018). Gender difference in equity crowdfunding: An exploratory analysis. *International Journal of Gender and Entrepreneurship*.

Mamonov, S., & Malaga, R. (2018). Success factors in title iii equity crowdfunding in the united states. *Electronic Commerce Research and Applications*, *27*, 65–73.

Mamonov, S., & Malaga, R. (2019). Success factors in title ii equity crowdfunding in the united states. *Venture Capital*, *21*(2-3), 223–241.

Meoli, M., & Vismara, S. (2021). Information manipulation in equity crowdfunding markets. *Journal of Corporate Finance*, *67*, 101866.

Motylska-Kuzma, A. (2018). Crowdfunding and sustainable development. *Sustainability*, *10*(12). https://doi.org/10.3390/su10124650

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, *13*(2), 187–221.

Nitani, M., Riding, A., & He, B. (2019). On equity crowdfunding: Investor rationality and success factors. *Venture Capital*, *21*(2-3), 243–272.

Palmatier, R. W., Houston, M. B., & Hulland, J. (2018). Review articles: Purpose, process, and structure.

Pascucci, F., Ancillai, C., & Cardinali, S. (2018). Exploring antecedents of social media usage in b2b: A systematic review. *Management Research Review*.

Petticrew, M., & Roberts, H. (2008). *Systematic reviews in the social sciences: A practical guide*. John Wiley & Sons.

Piva, E., & Rossi-Lamastra, C. (2018). Human capital signals and entrepreneurs' success in equity crowdfunding. *Small Business Economics*, *51*(3), 667–686.

Pret, T., & Cogan, A. (2018). Artisan entrepreneurship: A systematic literature review and research agenda. *International Journal of Entrepreneurial Behavior & Research*.

Ralcheva, A., & Roosenboom, P. (2020). Forecasting success in equity crowdfunding. *Small Business Economics*, *55*(1), 39–56.

Rossi, A., Vismara, S., & Meoli, M. (2019). Voting rights delivery in investment-based crowdfunding: A cross-platform analysis. *Journal of Industrial and Business Economics*, *46*(2), 251–281.

Sadiku-Dushi, N., Dana, L.-P., & Ramadani, V. (2019). Entrepreneurial marketing dimensions and smes performance. *Journal of Business Research*, *100*, 86–99.

Sapienza, H. J., & Gupta, A. K. (1994). Impact of agency risks and task uncertainty on venture capitalist–ceo interaction. *Academy of Management journal*, *37*(6), 1618–1632.

Scarmozzino, E., Corvello, V., & Grimaldi, M. (2017). Entrepreneurial learning through online social networking in high-tech startups. *International Journal of Entrepreneurial Behavior & Research*.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American economic review*, 465–479.

Schmitz, A., Urbano, D., Dandolini, G. A., de Souza, J. A., & Guerrero, M. (2017). Innovation and entrepreneurship in the academic setting: A systematic literature review. *International Entrepreneurship and Management Journal*, *13*(2), 369–395.

Securities, Commission, E. et al. (2016). Jumpstart our business startups (jobs) act.

Shafi, K. (2021). Investors' evaluation criteria in equity crowdfunding. *Small Business Economics*, *56*(1), 3–37.

Shane, S., & Cable, D. (2002). Network ties, reputation, and the financing of new ventures. *Management science*, *48*(3), 364–381.

Sorenson, O., & Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American journal of sociology*, *106*(6), 1546–1588.

Spence, M. (1973). L the mit press. *The Quarterly Journal of Economics*, *87*(3), 355–374.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British journal of management*, *14*(3), 207–222.

Troise, C. et al. (2019). Entrepreneurship and equity crowdfunding: Does it matter? *International Journal of Business and Management*, *14*(10), 72–86.

Usman, S. M., Bukhari, F. A. S., Usman, M., Badulescu, D., & Sial, M. S. (2019). Does the role of media and founder's past success mitigate the problem of information asymmetry? evidence from a uk crowdfunding platform. *Sustainability*, *11*(3), 692.

Vismara, S. (2016). Equity retention and social network theory in equity crowdfunding. *Small Business Economics*, *46*(4), 579–590.

Vismara, S. (2018). Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice*, *42*(3), 467–497.

Vismara, S. (2019). Sustainability in equity crowdfunding. *Technological Forecasting and Social Change*, *141*, 98–106.

Vrontis, D., Christofi, M., Battisti, E., & Graziano, E. A. (2020). Intellectual capital, knowledge sharing and equity crowdfunding. *Journal of Intellectual Capital*.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management*, *33*(6), 1237–1266.

Vulkan, N., Åstebro, T., & Sierra, M. F. (2016). Equity crowdfunding: A new phenomena. *Journal of Business Venturing Insights*, *5*, 37–49.

Wald, A., Holmesland, M., & Efrat, K. (2019). It is not all about money: Obtaining additional benefits through equity crowdfunding. *The Journal of Entrepreneurship*, *28*(2), 270–294.

Walthoff-Borm, X., Schwienbacher, A., & Vanacker, T. (2018). Equity crowdfunding: First resort or last resort? *Journal of Business Venturing*, *33*(4), 513–533.

Walthoff-Borm, X., Vanacker, T. R., & Collewaert, V. (2018). Equity crowdfunding, shareholder structures, and firm performance. *Corporate Governance: An International Review*, *26*(5), 314–330.

Waltman, L. (2016). A review of the literature on citation impact indicators. *Journal of informetrics*, *10*(2), 365–391.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS quarterly*, xiii–xxiii.

Xiao, L. (2019). How lead investors build trust in the specific context of a campaign: A case study of equity crowdfunding in china. *International Journal of Entrepreneurial Behavior & Research*.

Zhang, D., Li, Y., Wu, J., & Long, D. (2019). Online or not? what factors affect equity crowdfunding platforms to launch projects online in the pre-investment stage? *Entrepreneurship Research Journal*, *9*(2).

Part III

Study two

Chapter 3

Tapping the crowd for equity and herd behavior: a discrete choice experiment to elicit willingness-to-invest

"Live the full life of the mind, exhilarated by new ideas,
intoxicated by the romance of unusual."
[Ernest Hemingway]

Abstract

Based on theories of herd behaviour and information cascade, this paper investigates features that affect individuals' willingness to invest (WTI) in equity crowdfunding (ECF). Six main hypotheses were developed according to different levels of prior information set of crowd-investors.

An online survey containing a discrete choice experiment (DCE) was administered to 202 participants. Attributes and levels of alternative choices are constructed by evidence of both existing literature and empirical data of investment campaigns, randomly chosen among different ECF platforms. Fourteen choice sets are generated via a D-efficient fractional factorial design of the experiment and then placed into two parallel DCE's blocks, to ease the cognitive effort for participants. Stated preferences of participants are then analysed through conditional logit model and mixed logit model.

Results of the econometric models indicate that individuals tend to rely on pre-money valuations made by advisors, on decisions of professional investors, as well as on wisdom-of-the-crowd and social media. These findings support the deduction that herding ac-

cording to better informed parties can increase their information set and improve their decision-making between investment alternatives.

Implications are different according to individual or aggregate perspectives. On the one hand, at the level of the singular crow-investor, our results indicate that what is known as a "behavioural bias" turn out to be a "rational" behaviour, because she/he easily maximizes the personal available information set by following choices of more informed/skilled investors. On the other hand, at the level of the aggregated choices implications are two-sided: if the information at the top of the cascade (i.e. disseminated by entrepreneurs or analysts) is a genuine and reliable information, the market as a whole benefits from it, with an increase in the levels of allocative efficiency of the financing system via ECF. However, the other side of the coin testifies an increase of market systemic risks because manipulations (or simply errors) at the (same) top steps of the cascade inevitably propagate among less informed and skilled investors.

Keywords: *Equity crowdfunding, herd behavior, information cascade, stated preferences, discrete choice experiment*

3.1 Introduction

Equity crowdfunding (hereafter ECF) is a recent and innovative way for new ventures to obtain alternative financing (Agrawal et al., 2014). It consists in raising capital from a wide range of investors by issuing ownership shares via an open call over the internet supervised by a digital ECF platform. The process is similar to an initial public offering (IPO), where a firm raises financing via an equity issuance on primary markets. The two processes are however distinct in that ECF generally involves new ventures, considered high-risk nascent businesses (Mollick, 2014; Vulkan et al., 2016), and is open to everyone who is willing to invest via an easy open call on specialized webpage. The main players of an IPO, instead, are commonly mature firms, Stock Exchanges and financial intermediaries, within a more experienced marketplace. Nevertheless, both the processes are affected by information asymmetry between investors and firms/entrepreneurs representing investment opportunities.

Due to the nature of crowd-investors, ECF platforms act as intermediaries and try to facilitate funding for promising projects (Agrawal et al., 2016; Löher, 2017) in a double way. Firstly, they operate an ex-ante thorough due diligence and screening of new ventures that are looking for ECF listing (Löher, 2017). Only after this initial examination, the most promising projects are selected by the ECF platforms to obtain access to the fundraising campaign. Secondly, ECF platforms make available an ample set of information on the campaigns' webpage (Löher, 2017), providing both hard and soft information about the new venture and its management (Liberti and Petersen, 2019).

Beside this, ECF investors are typically small (in terms of investment size) and unsophisticated retail investors, often even novices, with none or scarce financial expertise. Despite the platforms' effort, information asymmetry between new ventures and the crowd is still present, due also to the riskiness of the investment (Vulkan et al., 2016). Therefore, crowd-investors need to cope with better-informed, and/or more skilled, parties to further downscale this asymmetry, improve their decision-making and select new venturing opportunities that should adequately reward the risk faced. Therefore, it is reasonable to argue that an information cascade could be the process through which individuals can increase their information set by observing better-informed parties (Bikhchandani et al., 1992).

In fact, the ECF environment ease information sharing and cascade (Vismara, 2018), as campaigns' websites hold a wide set of transparent information and live updates about projects (Ahlers et al., 2015).

The main assumption of this study is that information can come from various sources, based on both different proximity to the venture and degree of reliability about the project expected outcomes, resulting into a hierarchical cascade upon which crowd-investors tend to assume a herd behavior. Based on literature and empirical observation of the ECF campaigns, we state the following information cascade: (1) entrepreneurs, (2) analysts/advisors, (3) professional investors, (4) crowd of investors, (5) social media network, (6) cultural and geographical proximity. In this way, crowd-investors are able to learn information from top-levels of the information cascade (i.e. better-informed parties such as entrepreneurs, analysts, professional investors, etc.) up to the lower levels.

Here, we investigate if ECF investors assume a herd behavior to take superior decisions (Schwienbacher and Larralde, 2012), following an information cascade. So, we analyze the features that affect crowd-investors' willingness to invest (WTI) in ECF projects via a discrete choice experiment (DCE), based on an information set organized by the cascade that should guide expected herd behaviors, spread among ECF investors.

This work is organized as follows. The next section presents the theoretical background and sets the stage for the experiment. Then, the methodological procedure is thoroughly outlined. Next, the main findings and discussion are debated before drawing the conclusions.

3.2 Theoretical background

3.2.1 Information asymmetry, information cascades and herding in ECF

ECF investments might be interpreted within a principal-agent frame (Jensen and Meckling, 1976) and the contract theory, where the agents (the founders) are better informed about the quality/risk of the business project and the principals (crowd-investors) are not informed about the investments' outlook. Early-stage financing schemes are particularly affected by information asymmetries that can lead to suboptimal allocation of capital and market imperfections (J. E. Stiglitz and Weiss, 1981, J. Stiglitz and Weiss, 1983). Therefore, on one hand founders should signal the true quality/risk of the new venture (Spence, 2002) and provide as much information as possible to attract the crowd of investors. On the other hand, principals must rely on observable and available information to form their beliefs. Following their (often limited) information set, they assess investment opportunities and pick the ECF campaign in which they are willing to invest expecting that it can yield some returns.

Neoclassic economic theory implies strict and unrealistic hypothesis about investors' rationality and their ability to distinguish promising investments, who are instead prone to cognitive deviations and frictions (Baltussen, 2009). Indeed, crowd-investors are subject to bounded rationality (Simon, 1955), as they likely face limited abilities and expertise to evaluate projects (Ahlers et al., 2015) as well as an incomplete information set. Bounded rationality intervenes in the fact that individuals are not provided with perfect rationality nor perfect information elaboration skills (Hornuf and Schwienbacher, 2018). Therefore, market participants use mental shortcuts (heuristics) to ease complex decision-making and reach a satisfactory solution. Even though sometimes heuristics can lead to effective choices, they are prone to systematic errors and cognitive biases (Tversky and Kahneman, 1974).

Consequently, human decision-making does not turn choices to optimal solutions or to pareto efficiency, but rather to satisfactory alternatives (Simon, 1955). According to Nitani et al. (2019), it is essential that crowd-investors are not discouraged from ECF after they encounter bad experiences because of their investment choices, otherwise the ECF market will likely suffer from funds shortage. Therefore, crowd-investors need to pursue effective ways to improve their decision-making, which among all are either to acquire more pieces of information or, analogously, to follow parties that are believed to possess wider information sets. The latter is commonly referred to as herding or herd behavior and refers to the tendency of individuals to emulate the behavior of others, or adapt beliefs and choices to those that are believed to be better-informed or to individuals belonging to a membership (Bikhchandani and Sharma, 2000).

The economic theory of herding is split in two fields: herd behavior in non-market context (Bikhchandani et al., 1998) and in market context of asymmetric information, where the decision-maker emulates a better-informed party (Scharfstein and Stein, 1990). Concerning the latter scenario, theory shows that agents can take advantage of information aggregation from better-informed individuals to improve efficiently their information set (Grossman and Stiglitz, 1976). The process of aggregating information by observing other individuals is referred to as social learning (Bandura and Walters, 1977). Financial literature has imported this concept from psychology and developed it in terms of information cascade (Welch, 1992), which is a similar but distinct phenomenon from herding (Çelen and Kariv, 2004), and is based on the sequentiality of decision-making (Bikhchandani et al., 1992).

Equity crowdfunding is an ideal scenario for observing the information cascade phenomenon among the crowd of investors for many reasons (Vismara, 2018). Among all, the high-risk and uncertainty peculiarity of ECF campaigns, the lack of skills and expertise to evaluate the quality of projects, and high monitoring costs make herding and information cascades effective mechanisms for unsophisticated investors to undertake funding choices under imperfect information. Consequently, a key feature of ECF setting to downscale information asymmetries and select promising projects is the wisdom-of-crowds paradigm, which states the superiority of an average collective decision-making of groups of people compared to individual experts (Surowiecki, 2005).

3.2.2 Hypothesis development

We draw on herding behavior and information cascade experiment to investigate the features that affect crowd-investors' willingness to invest in ECF projects, after having updated their information sets by aggregating different pieces of information.

The main idea is that crowd-investors follow a herd behavior, according to a hierarchical information cascade, in the attempt to reduce information asymmetries, reduce risk and uncertainty, and downscale opaque information associated with cultural/geographical diversity, with the expectation of improving their decision-making and selecting promising projects.

We have disentangled the information cascade upon six different levels, according to the degree of informativeness of the additional source of information about business potentials.

The first source of information is provided by the entrepreneur(s), who knows better the true quality of her/his project. The entrepreneur(s) can signal her/his own commitment and self-confidence in her/his business idea by retaining equity shares after the offering (Vismara, 2016). The insider's financial involvement can be exploited as a practical tool used by outsiders (in this case, the ECF investors) to reduce information asymmetries. External stakeholders, in general, prefer founders who have made a significant, personal financial stake in their nascent ventures, known as “skin in the game” (Frid et al., 2015; Löher et al., 2018). The percentage of equity shares offered to the crowd, or similarly, the percentage of equity shares retained by the entrepreneur(s), are clearly visible pieces of information on ECF campaigns. Crowd-investors can deduce the real quality of the project by observing the commitment level of entrepreneurs, and possibly follow her/his lead.

> ***Hypothesis 1:*** *Crowd-investors' WTI in ECF campaigns decreases with the percentage of equity offered by entrepreneurs (i.e the external equity financing).*

Then, the pre-money valuation provides an estimate of the value of the new venture before raising equity crowdfunding financing. The information is provided by the entrepreneur her/himself on the campaign webpage, but it is evaluated by experts such as advisors or analysts who have access to a set of information and skills wider than investors; they can also possibly observe softer pieces of information about the entrepreneurial team and entrepreneurs themselves, as they cooperate with them to aggregate useful information in order to produce an objective pre-money valuation. Crowd-investors observe this value and are attracted by higher pre-money valuations as signals of good quality of the projects provided by better-informed parties (Löher et al., 2018).

> ***Hypothesis 2:*** *Crowd-investors' WTI in ECF campaigns increases with the current pre-money valuation of the new venture.*

Furthermore, the presence of professional investors reveals that more sophisticated investors with financial capabilities and expertise and/or investment institutions believe in the projects and supports it, often with larger pledges. Their presence is seen as a good quality signal by crowd-investors, who presume that professional investors have access to wider information sets. According to the information cascade theory they emulate their choices (Löher et al., 2018), resulting in a herd behavior.

> ***Hypothesis 3:*** *Crowd-investors' WTI in ECF campaigns increases with the presence of professional investors.*

Afterwards, the investment behavior of peers and thus of other crowd-investors could represent an effective signal that can be utilized as additional source of information to evaluate the quality of ECF campaigns. The information set of peers is not believed to be wider than professional investors or advisors/analysts or entrepreneurs themselves and is collocated in a lower position in the information cascade hierarchy. However, it is believed that the wisdom of the crowd can outperform the expertise and capabilities of individual experts (Surowiecki, 2005).

Hypothesis 4: *Crowd-investors' WTI in ECF campaigns acknowledge and follow the wisdom-of-the-crowd.*

This type of herd behavior can be observed from two perspectives: the number of current investors, and the percentage of funding amount raised on the target. The number of early investments made by the crowd and, thus, the number of investors can induce herding behavior and positively affect other investors' willingness to invest (Vulkan et al., 2016).

Hypothesis 4a: *the current number of investors increases crowd-investors' WTI in ECF campaigns.*

Similarly, the percentage of funding relates the capital raised to the minimum funding goal and signals the completion progress of the campaign, so that the decision-maker follows the wisdom of the crowd and is willing to invest in a specific project if the campaign is about to conclude successfully (Scharfstein and Stein, 1990).

Hypothesis 4b: *the current percentage of target capital raised increases crowd-investors' WTI in ECF campaigns.*

A less informative but still effective level of information cascade is represented by the social media network of the new venture or the entrepreneur, especially the number of connections on LinkedIn, since it provides an opportunity to downscale information asymmetries and validate less credible information (Nitani et al., 2019), as well as an endorsement of project quality (Shane and Cable, 2002)

Hypothesis 5: *Crowd-investors' WTI in ECF campaigns increases with the current number of connections on the LinkedIn profile of the entrepreneur.*

At the bottom of the hierarchical information cascade stands the geographic and cultural proximity. Although it may seem to shift the dynamic of the cascade since it does not add any real additional piece of information, it actually does induce herding behavior (Burtch et al., 2013).

Hypothesis 6: *Cultural and geographical proximity and similarity increases crowd-investors' WTI*

In particular, crowd-investors prefer to invest in campaigns within relatively close proximity, since they are more familiar with the country and the market in which the new venture is going to compete (Burtch et al., 2013; French and Poterba, 1991), recalling familiarity and home biases.

Hypothesis 6a: *Crowd-investors prefer to invest in domestic ECF campaigns over foreign ones.*

Similarly, the same effect applies for cultural proximity as it can induce higher level of initial trust and confidence in ECF campaigns from crowd-investors belonging to the same cultural group or citizenship (Burtch et al., 2013).

Hypothesis 6b: *Crowd-investors' WTI in ECF campaigns decreases with cultural/citizenship dissimilarity.*

3.3 Method: the discrete choice experiment (DCE)

3.3.1 Random utility theory and stated preferences

The strand of choice models aims at eliciting participants' preferences, namely possible investors, or consumers, via experiments of choice among alternatives. Two main approaches to elicit preferences can be followed: revealed preferences (Samuelson, 1938) and stated preferences (Louviere and Hensher, 1983). Discrete choice experiments (DCE) are based on the latter, so that participants are not asked to reveal the real utility or value associated to a choice, but instead are asked to state their preferred alternative among hypothetical choice scenarios (Ali and Ronaldson, 2012).

DCEs are commonly applied in the healthcare sector to evaluate preferences of patients and originated from a psychological study that investigated psychic stimuli (Thurstone, 1927). Later, the stimuli have been modeled as utility maximization (Marschak, 1960) and placed within the framework of the Random utility theory (RUT) for stated preferences. The RUT asserts that individuals facing choice dilemmas will pick the alternative that maximizes their perceived utility function based on a linear combination of preference weights and attributes (Train, 2003; McFadden et al., 1973).

Thanks to a survey administration, participants are asked to state their preferences between two hypothetical alternatives and a no-choice option, during a series of repeated but different scenarios/tasks, namely the choice sets of the experiments. Each alternative is characterized by a specific set of attributes, namely the characteristics chosen to define the alternatives, and attributes' levels, which are the different expressions of each attribute. Attributes can be dummy-coded, namely they are dichotomous and have only two attributes, or effect-coded, namely they vary within at least three different levels (generally from minimum to maximum in the case of an ordinal variable) or continuous.

Attributes are the same for the whole duration of the DCE, but their levels vary among the alternatives, to induce participants to make trade-offs and state their preferences (Pérez-Troncoso, 2020).

3.3.2 Attributes and levels

In order to build the DCE of this paper, we investigated both existing literature and empirical data by collecting pieces of information about the campaigns from the main ECF platforms, to determine thoroughly attributes and levels characterizing the alternatives from evidence (Ryan et al., 2001; Traets et al., 2020). Empirical evidence was randomly collected from different ECF campaigns among different platforms to identify plausible levels for each attribute.

We first determined the attributes by selecting the pieces of information, among the available information on ECF platforms, capable of generating herding behaviors according to existing literature. Indeed, for each project, platforms generally provide to investors a wide range of information such as: the business idea and business model, campaign round and current funding progress, entrepreneurs and team of founders, firm characteristics, financials and KPIs, links to social media, comments and updates about the project, a Q&A section and other documents available (usually upon request). The amount/extent of information provided varies from platform to platform.

We then similarly determined the levels of each attribute to reflect realistic and plausible investment alternatives (Coast and Horrocks, 2007). The number of attributes and levels is chosen as to do not discourage participants by requiring an excessive cognitive effort compromising the validity of the experiment (Mangham et al., 2009; F. R. Johnson et al., 2013). On average, DCEs use less than ten attributes and the majority uses

Level (source) of information cascade	***Attribute***	***Explanation to participants***	***Levels***
Entrepreneur	Percentage of equity offered	Percentage of firms' shares offered to future shareholders (in case of successful ECF campaign)	*5%* *15%* *98%*
Advisors/analysts	Pre-money valuation	Estimated valuation of the new venture before launching the ECF campaign	*10,000 €* *500,000 €* *1,000,000 €*
Professional investors	Presence of professional investors	Presence of professional investors (financial intermediaries, venture capitalists, business angels, etc.)	*Present* *Missing*
Wisdom-of-the-crowd	Number of investors	Number of current investors	*20* *100* *400*
Wisdom-of-the-crowd	Percentage of target capital raised	Percentage of capital already raised to the minimum financing target (the new venture will be financed on the condition that 100% is reached)	*15%* *90%* *110%*
Social media	Number of LinkedIn connections	Number of connections on the LinkedIn profile of the entrepreneur	*30* *160* *500+*
Proximity and familiarity	Geographical location	Registered office of the new venture	*Milan, IT* *London, GB* *Hong Kong, HK*

Table 3.1: Attributes, explanation and levels as presented to participants

between three and seven attributes (DeShazo and Fermo, 2002; Traets et al., 2020).

Thus, we generated alternatives of seven attributes, of which six with three levels and one as a dummy variable with two levels: percentage of equity offered, pre-money valuation, presence of professional investors, number of investors, percentage of capital raised, number of LinkedIn connections, geographical location (Tab. 3.1).

3.3.3 Experimental design

Having determined attributes and levels, choice sets are finally composed of two alternatives of hypothetical ECF campaigns and a no-choice alternative. This opt-out opportunity is given to make sure that participants are not forced to pick an alternative and it alleviates their cognitive burden (Krosnick et al., 2002; Traets et al., 2020).

The number of choice-sets to be presented to the participants is analogously crucial in designing the experiment. The set of all the possible combination of the attributes and levels would lead to 1.280.000.000 profiles (full factorial design, eq. 3.1).

$$full\,factorial = number\,of\,levels^{number\,of\,attributes} \tag{3.1}$$

A fractional factorial design, instead, generates a selection of the full factorial that consists of an efficient experimental design characterized by the properties of orthogonality, minimal overlap, level balance and utility balance (Huber and Zwerina, 1996). The most

choice set: 1 / 14

	Investment A	**Investment B**
Registered office	Hong Kong, HK	Milan, IT
Percentage of capital raised to minimum goal	90%	90%
Number of current investors	20	100
Presence of professional investors	Missing	Present
Percentage of equity offered to investors	5%	15%
Pre-money valuation of the new venture	10.000€	500.000€
Number of connections on the LinkedIn profile of the entrepreneur	500+	500+

I choose to invest in:

Investment A   Investment B   Do not invest

OK

Figure 3.1: Example of a choice set

statistically efficient design (D-optimal design) is the experimental design matrix that minimizes the standard errors of the estimated coefficients and is selected according to the D-efficiency measure (Street et al., 2005).

In this paper, the optimal design is obtained using the Idefix package (Traets et al., 2020) available in R language. We adopted the Coordinate Exchange Algorithm to produce the D-efficient design, since it is assumed to produce equally efficient designs as the Modified Fedorov algorithm for designs with more than ten choice sets (Traets et al., 2020). Indeed, the minimum number of choice sets generated by the fractional factorial design is given by *(l-k+1)*, where l is the number of levels and k the number of attributes, resulting in fourteen choice sets of two alternatives plus the no-choice option each. Figure 3.1 shows an example of a choice set sampled from the administered DCE and translated in English.

We also implemented a blocking procedure, by dividing the fourteen choice sets into two blocks, in order to lessen the mental effort asked to participants and improve the efficacy of their responses, so that each participant was randomly asked to choose among seven choice sets only (F. R. Johnson et al., 2013).

3.3.4 Sampling and data collection

The two blocks of efficiently generated choice-sets have been in parallel implemented into surveys created with Google Forms. The two surveys are organized into three main sections: section 1 contains socio-demographic questions, section 2 represents the DCE and the last section includes a set of control questions.

The surveys have been administered online in the period of May 2021 to Italian-speaking participants with a discrete response rate (approx. 70%), resulting in a sample size of N=202. According to a common rule of thumb, at least 56 observations were needed (eq 3.2; R. M. Johnson and Orme, 1996):

$$n \geq \frac{500c}{ta} \tag{3.2}$$

where n is the number of respondents, t is the number of choice sets, a is the number of alternatives per choice set (excluding the no-choice alternative) and c is the number of analysis cells that in our case (main effects coding) represented the largest number of levels per attribute.

Data collected from the Google Forms surveys has finally been resized, reshaped, and decoded via the R-studio software (R version 4.0.4) in order to run the econometric models.

3.3.5 Econometric models specification

According to the Random Utility Theory and the conditional logit model of McFadden et al. (1973), the utility function of a specific alternative for an individual (u_{ij}) is expressed as a linear combination of a deterministic (systematic) component (V_{ij}) and a random component (ε_{ij}), where the deterministic component (V_{ij}) is a function of a vector of attribute levels of the alternative j (X_j) and a vector of estimated coefficients (β_j) fixed for each individual (eq. 3.3).

$$u_{ij} = V_{ij} + \varepsilon_{ij} = V_{ij}(\beta_j, X_j) + \varepsilon_{ij} \tag{3.3}$$

The random (stochastic) component (ε_{ij}) is non-observable, thus the probability of choosing alternative j is given by eq. 3.4:

$$Pr(choice = j) = \frac{exp(V_{ij})}{\sum_{j=1}^{J} exp(V_{ij})} \tag{3.4}$$

However, conditional logit is based upon the strong assumptions that utility does not vary among participants but does vary among alternatives and of the *independence of irrelevant alternatives* (IIA). Conditional logit limitations can be overcome by the mixed logit mode (or random coefficients logit model, McFadden and Train, 2000), which is an extension of the conditional logit model of McFadden et al. (1973). The mixed logit model considers individual heterogeneities and relaxes the IIA assumption, by allowing for random taste variation, where the vector of estimated coefficients (β_{ij}) varies randomly among individuals. The utility function of participants will then be:

$$u_{ij} = V_{ij}(\beta_{ij}, X_j) + (n_{ij} + \varepsilon_{ij}) \tag{3.5}$$

where η_{ij} is a stochastic component with zero mean whose distribution depends from underlying parameters and observed data and ε_{ij} is independent and identically distributed (iid) (Hensher and Greene, 2003). Therefore, the unconditional (heterogeneity in individual preferences) probability of choosing alternative j is given by the following integration:

$$Pr(choice = j) = \int L_{ij}(\beta) f(\beta) d\beta, \quad where\, L_{ij} = \frac{exp(V_{ij})}{\sum_{j=1}^{J} exp(V_{ij})} \tag{3.6}$$

In this paper we first adopted a conditional logit model to model participants' preferences among alternatives and then we adopted the mixed logit model to account for individual's heterogeneity.

3.4 Findings

Description of the sample

The sample consisted of 202 observations, collected from the research team via online administration of Google Forms surveys in May 2021 with a response rate of about 70%.

The surveys have been randomly administered to individuals of Italian nationality, for two reasons. Firstly, because the DCE was translated into Italian and addressed to people in their mother tongue in order to ease their cognitive effort and make sure that their focus was entirely on the questions and choice experiment. Secondly, nationality heterogeneity within the sample could affect the validity of tests on hypothesis 6, which investigates the cultural and geographical proximity effect. Coherently, we need to exclude not Italian participants. The sample is equally split for gender, with a slight prevalence of female participants, and is mostly populated by digital-native participants (below 35 years old), perhaps more familiar with online surveys/experiments and digital innovation.

The majority of the sample comes from the central part of Italy and earns a middle-high income. The 44% of the participants are students, 58% possess some university degree and 44% of them are acquainted with economical or financial topics, although not required to avoid sampling bias, as crowd-investors are typically unsophisticated investors. Table 3.2 indicates the socio-demographic characteristics of participants.

3.4.1 Results of the choice models

We first adopted the conditional logit model (MNL, McFadden et al., 1973) to estimate parameters that affected the outcome of decision-making of participants, namely the binary choice variable. Explanatory variables are the effect coded attributes of the alternatives. Results are presented in table 3.3.

The model shows a concordance statistic of 0.6 with a 95% confidence interval above 0.5 (Harrell Jr et al., 1996). Results of the conditional logit model indicate that six out of seven attributes can be considered significant in the decision-making of individuals when choosing between the alternatives.

In particular, the geographical location of registered offices of the new ventures, instead, appears to be not significant in affecting ECF investment choices, as none of the levels of the attribute is significant.

The effect-coded variable "percentage of capital raised" is highly significant with $Pr(>|z|) < 0.001$ for the lower level of the attribute and negative sign of the coefficient. However, a campaign that has reached 90% of funding has a higher and significant likelihood to be chosen compared to the reference level of 110% of funding (overfunding) raised.

Characteristics	**Frequency**	**%**	**Characteristics**	**Frequency**	**%**
Gender			**Field of Study**		
Female	110	54.45%	Agriculture	4	1.98%
Male	92	45.54%	Business/commercial	2	0.99%
			Chemical/Pharmaceutical	4	1.98%
Age			Economics	77	38.11%
Less than 25	69	34.15%	Engineering	22	10.89%
25 – 34	99	49%	Finance	12	5.94%
35 – 44	10	4.95%	Healthcare	7	3.46%
45 – 54	15	7.42%	Humanistic studies	15	7.42%
55 – 64	8	3.96%	Information technology	7	3.46%
More than 64	1	0.49%	Languages	2	0.99%
			Law	12	5.94%
From			Psychology	2	0.99%
Northern Italy	19	9.40%	Science/Biology	10	4.95%
Central Italy	158	78.21%	Scientific/Maths	13	6.43%
Southern Italy	20	9.90%	Technical/professional	10	4.95%
Sicily/Sardinia	3	1.48%	Others	3	1.48%
Abroad	2	0.99%			
			Profession		
Income			Students	90	44.55%
Less than 1,000€	8	3.96%	Fixed-term contract	23	11.38%
1,000€ - 2,000€	48	23.76%	Permanent contract	51	25.24%
2,000€ - 4,000€	83	41.08%	Director/Executive	2	0.99%
4,000€ - 5,000€	13	6.43%	Freelance/Entrepreneurs	16	7.92%
More than 5,000€	21	10.39%	Unemployed	11	5.44%
Not declared	29	14.35%	Retired	3	1.48%
			Others	6	2.97%
Education					
Middle school	9	4.45%			
High school	66	32.67%			
Bachelor degree	62	30.69%			
Master's degree	55	27.22%			
Specialization course	8	3.96%			
Ph.D.	2	0.99%			

Table 3.2: Socio-demographic characteristics of participants (N=202)

The lower levels of the attribute concerning the number of current investors present both a negative and significant (for the lower only) sign, meaning that a positive effect on choice as the number of investors appreciably increases (400 investors already in the campaign) can be assumed.

The dummy variable that indicates the absence of professional investors is highly significant (at 0.001 level), meaning that when professional investors are missing, this causes a strong reduction in willingness to invest. Contrarily, the reference level in which professional investors are presents, is considered more attractive from participants. The percentage of equity offered from entrepreneurs to investors surprisingly shows a negative and significant sign for the lower level, thus an opposite effect on choice than expected

Variables	*Coefficients (Sig.)*	*Odds ratio*	*S.E. (Z)*	*P-value*
(Intercept)	-0.223 (***)	0.799	0.065 (-3.39)	0.000
Geographical location				
Milan, It	-0.058	0.943	0.056 (-1.03)	0.298
London, GB	0.067	1.070	0.054 (1.24)	0.213
Hong Kong, HK		— (omitted) —		
Percentage of capital raised				
15%	-0.372 (***)	0.689	0.058 (-6.31)	0.000
90%	0.176 (***)	1.192	0.054 (3.25)	0.001
110%		— (omitted) —		
Number of investors				
20	-0.123 (**)	0.883	0.062 (-1.97)	0.048
100	-0.021	0.978	0.055 (-0.39)	0.693
400		— (omitted) —		
Presence of professional investors				
Present		— (omitted) —		
Missing	-0.349 (***)	0.704	0.073 (-4.74)	0.000
Percentage of equity offered				
5%	-0.140 (**)	0.868	0.059 (-2.36)	0.017
15%	0.108 (*)	1.114	0.059 (1.81)	0.069
98%		— (omitted) —		
Pre-money valuation				
10,000€	-0.204 (***)	0.814	0.053 (-3.85)	0.000
500,000€	0.108 (*)	1.114	0.056 (1.91)	0.055
1,000,000€		— (omitted) —		
Number of connections on social media				
30	-0.155 (**)	0.856	0.065 (-2.36)	0.017
160	0.022	1.022	0.058 (0.38)	0.698
500+		— (omitted) —		
N = 4242, number of events = 1414				
Concordance = 0.595 (se = 0.014)				
Likelihood ratio test = 124.3 on 14 df, p=<0.000				
Wald test = 114.7 on 14 df, p=<0.000				
Score (logrank) test = 121.6 on 14 df, p=<0.000				
* Statistical significance at the 10% level.				
** Statistical significance at the 5% level.				
*** Statistical significance at the 1% level.				

Table 3.3: Results of the conditional logit model

from the hypothesis. However, the middle level of 15% of equity offered shows a positive effect on choice if compared to the reference level of 98% of equity offered, although weakly significant ($Pr(> |z|) < 0.1$).

Pre-money valuation is highly significant and valued positively from the participants, showing a negative effect for the lower level of the attribute.

Analogously, the connections on the Linkedin profile of the entrepreneur seem to encourage participations, as the number appreciably increases.

In fact, the lower level of connections shows a negative and significant effect on choice if compared to the reference level of 500+ connections, recalling that LinkedIn private profiles that have more than 500 connections do not show the real number of followers, but rather the label "500+". Since we can expect a certain degree of heterogeneity among

Variables	***Coefficients (Sig.)***	***S.E. (Z)***	***P-value***	***Standard deviation estimates (Sig.)***
(Intercept)	-0.203 (***)	0.075 (-2.68)	0.007	
	Geographical location			
Milan, It	-0.056	0.064 (-0.88)	0.378	0.042
London, GB	0.047	0.065 (0.72)	0.468	0.014
Hong Kong, HK	— (omitted) —			
	Percentage of capital raised			
15%	-0.491 (***)	0.078 (-6.27)	0.000	0.551 (***)
90%	0.216 (***)	0.063 (3.39)	0.000	-0.155
110%	— (omitted) —			
	Number of investors			
20	-0.146 (**)	0.073 (-1.99)	0.045	0.446 (***)
100	-0.009	0.066 (-0.14)	0.885	0.225
400	— (omitted) —			
	Presence of professional investors			
Present	— (omitted) —			
Missing	-0.608 (***)	0.118 (-5.12)	0.000	1.188 (***)
	Percentage of equity offered			
5%	-0.213 (***)	0.073 (-2.89)	0.003	-0.064
15%	0.118 (*)	0.071 (1.64)	0.099	-0.040
98%	— (omitted) —			
	Pre-money valuation			
10,000€	-0.214 (***)	0.066 (-3.24)	0.001	0.313 (**)
500,000€	0.075	0.066 (1.12)	0.258	-0.022
1,000,000€	— (omitted) —			
	Number of connections on social media			
30	-0.142 (*)	0.076 (-1.86)	0.062	-0.180
160	0.020	0.067 (0.30)	0.763	-0.044
500+	— (omitted) —			

Frequencies of alternatives: choice
1 2 3
36.4% 32.1% 31.4%
BFGS method
22 iterations
Log-Likelihood: -1459.3 (df=27)

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

Table 3.4: Results of the mixed logit model

the decision-making of participants, we implemented a mixed logit model (MMNL; McFadden and Train, 2000) to overcome limitations to the estimates of the conditional logit model. Mixed logit model is used to estimate parameters that affected the choice dependent variable of participants, based on the attributes used as effect-coded explanatory variables whose coefficients are assumed to be randomly distributed (Gaussian distribution). Results are presented in table 3.4.

The model indicates that preference heterogeneity is present, since some standard deviations estimates are large and significant. In particular, the attributes concerning the presence of professional investors, the percentage of capital raised, the number of current investors and pre-money valuation of the startup present considerable preference heterogeneity among individuals.

Nevertheless, the coefficient estimates of the variables are in line with those of the conditional logit model, with the exception of the number of connections on the LinkedIn profile whose significance appears weakened.

The percentage of capital raised and the presence of professional investors increase both impact and significance with individual heterogeneity.

3.5 Discussion: impact of herding on crowd-investors' choices

Hypotheses and sub-hypotheses	***Model 1 (MNL)***	***Model 2 (MMNL)***
H1: Crowd-investors' WTI in ECF campaigns decreases with the percentage of equity offered by entrepreneurs (i.e the external equity financing)	Partially supported	Partially supported
H2: Crowd-investors' WTI in ECF campaigns increases with the current pre-money valuation of the new venture	Supported	Supported
H3: Crowd-investors' WTI in ECF campaigns increases with the presence of professional investors.	Supported	Supported
H4: Crowd-investors' WTI in ECF campaigns acknowledge and follow the wisdom-of-the-crowd.	Partially supported	Partially supported
H4a: the current number of investors increases crowd-investors' WTI in ECF campaigns.	Partially supported	Partially supported
H4b: the current percentage of target capital raised increases crowd-investors' WTI in ECF campaigns.	Partially supported	Partially supported
H5: Crowd-investors' WTI in ECF campaigns increases with the current number of connections on the LinkedIn profile of the entrepreneur	Partially supported	Partially supported
H6: Cultural and geographical proximity and similarity increases crowd-investors' WTI	Not supported	Not supported
H6a: Crowd-investors prefer to invest in domestic ECF campaigns over foreign ones.	Not supported	Not supported
H6b: Crowd-investors' WTI in ECF campaigns decreases with cultural/citizenship dissimilarity.	Not supported	Not supported

Table 3.5: Research hypotheses testing

Results from the models indicate that four hypotheses out of six appear to be supported or partially supported (Tab. 3.5). In particular, hypotheses 2 and 3 are supported by evidence from our sample and hypotheses 1, 4 and 5 are partially supported, even though H5 loses some significance when accounting for individual heterogeneity, whether hypothesis 6 is not supported at all in this sample.

In terms of interpretation, our results indicate that heterogeneity among individuals' preferences is present and that participants tend to give more credibility to pre-money valuations made by advisors/analysts and to investment decisions of professional investors, supporting evidence support to research hypotheses 2 and 3. Thus, participants to the experiment assumed that undertaking a herd behavior according to the signals provided by advisors/analysts and professional investors can improve their selection of promising ECF projects, as they are considered trustworthy parties who possess wider information sets.

More specifically, participants to the experiment tend to be attracted by campaigns that offer 15% of equity shares to the crowd, rather than a higher amount (98%), giving credit to entrepreneurs for proving own commitment in the project and skin-in-the-game, as in Löher et al. (2018). Hypothesis 1 is however only partially supported since the likelihood of choosing the lower level (5%) of equity offered presents a negative (contradictory) and significant coefficient if compared to the reference level of 98%. This effect indicates a preference for higher stakes, which partially contradicts the hypothesis, and could be interpreted as the intrinsic motivation of crowd-investors to be part of the project to receive personal gain, as for Wald et al. (2019). Alternatively, perhaps, as resulting from Lukkarinen et al. (2016), unsophisticated investors might have different criteria of evaluation of the investment alternatives from sophisticated and professional investors. It is an interesting result that should be analyzed further.

The pre-money valuation (H2) indicates the estimate of the value of the new venture before obtaining ECF financing made by an expert (analyst or advisor). Crowd-investors tend to give importance to this source of information and prefer campaigns with higher valuations and results in line with Löher et al. (2018). In fact, participants to the experiment were discouraged by investment alternatives with lower pre-money valuations (10,000€) and on the contrary followed the lead of advisors/analysts who released good quality signals by assigning higher pre-money valuations (1,000,000€).

The presence of professional investors (H3) reveals that an investment institution (Venture Capitalist, Business Angel, Financial Intermediary, etc.) believes in the projects and supports it, often with larger resources, and attracts crowd-investors as in Kleinert et al. (2020), whether their absence is often seen as a bad quality signal. Crowd-investors consider this piece of information valuable and tend to follow professional investors, as they likely possess more sophisticated selection criteria of the projects as demonstrated by Lukkarinen et al. (2016).

According to Polzin et al. (2018), participants tend also to rely on the wisdom-of-the-crowd, assuming that the community of investors can make more effective choices of promising projects. At this level, herd behavior is present: hypothesis 4 is partially supported. Number of investors (H4a) affect individuals' decision-making in that a lower value discourage participants to choose the alternative, whether they are attracted by projects in which an ample crowd of investors is already investing, in line with findings of Vulkan et al. (2016). The partial support to the hypothesis is perhaps given by the fact that there is no appropriate value for the number of investors to persuade them to invest, as the middle level (100) appears negligible and non-significant. Perhaps, participants do not particularly rely on a cardinal measure of the wisdom-of-the-crowd, but rather on an ordinal one. Indeed, the number of investors is an absolute value whose impact depends on the size of the project and on the target capital and can be perceived differently according to the alternatives. When shifting to the percentage of capital raised (H4b), which is a weighted measure of the number of investors, herd behavior is supported by stronger significance of the estimates, as participants' stated preferences address campaigns that are close to reach the funding goal, rather than campaigns with lower amounts of capital raised. However, the likelihood of choosing an alternative that has raised 90% of capital, rather than 110%, is positive and highly significant. This result indicates that crowd-investors are more likely to invest in ECF campaigns that has already raised a higher amount of capital from the crowd, but perhaps still needs to reach the funding goal, so that they can contribute with their resources to achieve it and feel part of the success of a campaign, in line with Wald et al. (2019). Indeed, the sense of belonging and social identification with the equity crowdfunding community that made possible the successful funding of a project is a non-marginal intrinsic motivation for crowd-investors (Popescul et al., 2020).

Hypothesis 5 indicates that participants prefer alternatives that show the highest value of connections, which is bounded above by the label "500+", to alternatives with poor LinkedIn connections (30), whether the middle level (160) seems to have no effect (non-significant and negligible). In other words, popularity of entrepreneurs on social media, expressed as the number of connections on their LinkedIn profile, seems to attract more crowd-investors (H5). It is perceived as a signal of higher level of trust about project quality endorsed by the social media network (Shane and Cable, 2002), inducing herding among the community of crowd-investors.

Hypothesis 6 is not supported by evidence of our sample and the coefficient estimates of the levels are both negligible and non-significant; therefore, we cannot state whether the geographical (H6a) or cultural (H6b) proximity can affect the decision-making among alternatives. This aspect should be analyzed further to identify potential patterns of investment preferences for certain geographical locations/cultures (Ralcheva and Roosenboom, 2016) that might be considered by the crowd as more effective in facilitating new ventures.

As a concluding remark on the interpretation of results, from our study emerges that a herd behavior appears to be effective according to an information cascade from the entrepreneurs (top level) up to the level of social media network (the fifth step of the cascade). In other words, unsophisticated crowd-investors attempt to reduce information asymmetry about the trustworthiness and true quality of ECF projects by aggregating different pieces of information that can be learned from various sources. Valuable information can, thus, be deducted by the behavior of (and not necessarily in this order): (i) entrepreneurs, (ii) advisors/analysts, (iii) professional investors, (iv) crowd of investors, (v) social media network. The main idea is that their behavior can be interpreted as an effective signal and contribute to improve the information set of decision-makers, who are able in this way to downsize investment risk and pick more promising projects by following the lead of better-informed parties.

3.6 Conclusions

This study is based on information cascade and herding in equity crowdfunding as a process to downscale asymmetric information by increasing the information set of crowd-investors from better-informed parties. ECF is the process, similar to an IPO, through which a new venture is able to raise financing via an equity offering over the internet to an ample crowd of investors.

The nature of crowd-investors implies that ECF platforms must establish a transparent environment by making available as much information as possible and must ease information sharing. Nevertheless, information asymmetries might persist, and crowd-investors could undertake herding techniques to update their information set by observing better-informed or skilled parties.

We collected data of 202 observations from a survey administration and investigated it via a discrete choice experiment in order to investigates ECF campaigns' attributes that affect crowd-investors' willingness to invest. These attributes were related to a set of hypotheses on the presence of herd behaviors based on an information cascade. Results indicate that participants attempt to reduce information asymmetry by aggregating and deriving pieces of information from different sources according to the assumed information cascade. Even if heterogeneity among individuals is relevant, participants tend to consider particularly trustworthy information deduced from analysts and professional investors. Herd behavior is supported by evidence also with reference to entrepreneurs, the wisdom-of-the-crowd and social media network. Conversely, geographical and cultural proximity instead found no support from evidence. Overall, we can conclude that individuals undertake herding techniques to update their information set by observing better-informed or skilled parties, basically following an information cascade.

However, a main issue remains still open: is herding a good or bad behavior/attitude for investors willing to invest in ECF? Although herd behavior is sometimes seen with a negative meaning as a behavioral bias (herd bias or herd mentality bias), it actually turns out to be a "rational" heuristic (Gigerenzer, 2018), because individuals easily maximize the personal available information set by following choices of more informed/skilled investors.

Implications are thus different according to individual or aggregate perspectives. On the one hand, at the level of the singular crow-investor, she/he is able to update her/his information set and choose more promising projects through herding. On the other hand, at the level of the aggregated choices implications are two-sided: if the information at the top of the cascade (i.e. disseminated by entrepreneurs or analysts) is a genuine and reliable information, the market as a whole benefits from it, with an increase in the levels of allocative efficiency of the financing system via ECF. However, the flipside testifies an increase of market systemic risks because manipulations (or simply errors) at the (same) top steps of the cascade inevitably propagate easily among less informed and skilled investors.

Possible safeguards to systemic risks derive from the role of both ECF platforms and regulators. The former, acting as financial intermediaries and syndicates, are able to downscale systemic risk and have the incentive to select and public only the most promising campaigns. The latter have the duty not only to (and not limited to) ensure the transparency and reliability of information, which can anyway be genuinely biased by mere prediction errors (i.e. analysts that miss the plausible pre-money valuation or professional investors that bet on an unpromising project), but also (and most importantly) to induce among crowd-investors awareness of their behavior within financial settings and encourage portfolio diversification and financial literacy.

We recognize the limitations of the study which could be threefold. In the first place, the sample is composed solely of Italian participants, a choice supported by specific reasons, but with a drawback linked to cultural heterogeneity that could guide our results. Secondly, the majority of participants are students, and it would be interesting to study the stated preferences of practitioners or actual crowd-investors, instead. Thirdly, the nature of the experimental design could deviate from the actual (revealed) preferences of individuals, as DCEs are based on stated preferences.

Nevertheless, the same limits open enlighten further research where these experiments could be administered to different countries/cultures and/or to practitioners or crowd-investors to investigate whether they state similar preferences. Besides, a promising future research could compare results obtained withing an experimental design with real-life investors decisions in ECF platforms.

References for Chapter 3

Agrawal, A., Catalini, C., & Goldfarb, A. (2014). Some simple economics of crowdfunding. *Innovation Policy and the Economy*, *14*(1), 63–97. https://EconPapers.repec.org/RePEc:ucp:ipolec:doi:10.1086/674021

Agrawal, A., Catalini, C., & Goldfarb, A. (2016). Are syndicates the killer app of equity crowdfunding? *California management review*, *58*(2), 111–124.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship theory and practice*, *39*(4), 955–980.

Ali, S., & Ronaldson, S. (2012). Ordinal preference elicitation methods in health economics and health services research: Using discrete choice experiments and ranking methods. *British medical bulletin*, *103*(1), 21–44.

Baltussen, G. (2009). Behavioral finance: An introduction. *Available at SSRN 1488110*.

Bandura, A., & Walters, R. H. (1977). *Social learning theory* (Vol. 1). Englewood cliffs Prentice Hall.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, *100*(5), 992–1026.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1998). Learning from the behavior of others: Conformity, fads, and informational cascades. *Journal of economic perspectives*, *12*(3), 151–170.

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff papers*, *47*(3), 279–310.

Burtch, G., Ghose, A., & Wattal, S. (2013). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. *Information Systems Research*, *24*(3), 499–519.

Çelen, B., & Kariv, S. (2004). Distinguishing informational cascades from herd behavior in the laboratory. *American Economic Review*, *94*(3), 484–498.

Coast, J., & Horrocks, S. (2007). Developing attributes and levels for discrete choice experiments using qualitative methods. *Journal of health services research & policy*, *12*(1), 25–30.

DeShazo, J., & Fermo, G. (2002). Designing choice sets for stated preference methods: The effects of complexity on choice consistency. *Journal of Environmental Economics and management*, *44*(1), 123–143.

French, K. R., & Poterba, J. M. (1991). Investor diversification and international equity markets.

Frid, C. J., Wyman, D. M., & Gartner, W. B. (2015). The influence of financial'skin in the game'on new venture creation. *Academy of Entrepreneurship Journal*, *21*(2), 1.

Gigerenzer, G. (2018). The heuristics revolution: Rethinking the role of uncertainty in finance. *The behavioural finance revolution*. Edward Elgar Publishing.

Grossman, S. J., & Stiglitz, J. E. (1976). Information and competitive price systems. *The American Economic Review*, *66*(2), 246–253.

Harrell Jr, F. E., Lee, K. L., & Mark, D. B. (1996). Multivariable prognostic models: Issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Statistics in medicine*, *15*(4), 361–387.

Hensher, D. A., & Greene, W. H. (2003). The mixed logit model: The state of practice. *Transportation*, *30*(2), 133–176.

Hornuf, L., & Schwienbacher, A. (2018). Market mechanisms and funding dynamics in equity crowdfunding. *Journal of Corporate Finance*, *50*, 556–574.

Huber, J., & Zwerina, K. (1996). The importance of utility balance in efficient choice designs. *Journal of Marketing research*, *33*(3), 307–317.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), 305–360.

Johnson, F. R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D. A., Bresnahan, B. W., Kanninen, B., & Bridges, J. F. (2013). Constructing experimental designs for discrete-choice experiments: Report of the ispor conjoint analysis experimental design good research practices task force. *Value in health*, *16*(1), 3–13.

Johnson, R. M., & Orme, B. K. (1996). How many questions should you ask in choice-based conjoint studies. *Art Forum, Beaver Creek*, 1–23.

Kleinert, S., Volkmann, C., & Grünhagen, M. (2020). Third-party signals in equity crowdfunding: The role of prior financing. *Small Business Economics*, *54*(1), 341–365.

Krosnick, J. A., Holbrook, A. L., Berent, M. K., Carson, R. T., Michael Hanemann, W., Kopp, R. J., Cameron Mitchell, R., Presser, S., Ruud, P. A., Kerry Smith, V., et al. (2002). The impact of" no opinion" response options on data quality: Non-attitude reduction or an invitation to satisfice? *Public Opinion Quarterly*, *66*(3), 371–403.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1–41.

Löher, J. (2017). The interaction of equity crowdfunding platforms and ventures: An analysis of the preselection process. *Venture Capital*, *19*(1-2), 51–74.

Löher, J., Schneck, S., & Werner, A. (2018). A research note on entrepreneurs' financial commitment and crowdfunding success. *Venture Capital*, *20*(3), 309–322.

Louviere, J. J., & Hensher, D. A. (1983). Using discrete choice models with experimental design data to forecast consumer demand for a unique cultural event. *Journal of Consumer research*, *10*(3), 348–361.

Lukkarinen, A., Teich, J. E., Wallenius, H., & Wallenius, J. (2016). Success drivers of online equity crowdfunding campaigns. *Decision Support Systems*, *87*, 26–38.

Mangham, L. J., Hanson, K., & McPake, B. (2009). How to do (or not to do)... designing a discrete choice experiment for application in a low-income country. *Health policy and planning*, *24*(2), 151–158.

Marschak, J. (1960). Binary choice constraints on random utility indications in: Arrow k, editor. *Stanford Symposium on Mathematical Methods in the Social Sciences: Stanford University Press.[Google Scholar]*.

McFadden, D. et al. (1973). Conditional logit analysis of qualitative choice behavior.

McFadden, D., & Train, K. (2000). Mixed mnl models for discrete response. *Journal of applied Econometrics*, *15*(5), 447–470.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of business venturing*, *29*(1), 1–16.

Nitani, M., Riding, A., & He, B. (2019). On equity crowdfunding: Investor rationality and success factors. *Venture Capital*, *21*(2-3), 243–272.

Pérez-Troncoso, D. (2020). A step-by-step guide to design, implement, and analyze a discrete choice experiment. *arXiv preprint arXiv:2009.11235*.

Polzin, F., Toxopeus, H., & Stam, E. (2018). The wisdom of the crowd in funding: Information heterogeneity and social networks of crowdfunders. *Small Business Economics*, *50*(2), 251–273.

Popescul, D., Radu, L. D., Păvăloaia, V. D., & Georgescu, M. R. (2020). Psychological determinants of investor motivation in social media-based crowdfunding projects: A systematic review. *Frontiers in Psychology*, 3676.

Ralcheva, A., & Roosenboom, P. (2016). On the road to success in equity crowdfunding. *Available at SSRN 2727742*.

Ryan, M., Bate, A., Eastmond, C. J., & Ludbrook, A. (2001). Use of discrete choice experiments to elicit preferences. *BMJ Quality & Safety*, *10*(suppl 1), i55–i60.

Samuelson, P. A. (1938). A note on the pure theory of consumer's behaviour. *Economica*, *5*(17), 61–71.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American economic review*, 465–479.

Schwienbacher, A., & Larralde, B. (2012). Crowdfunding of small entrepreneurial ventures. *In Cumming, D. (Ed.) "The Oxford handbook of entrepreneurial finance.", Oxford University Press,* 369–391.

Shane, S., & Cable, D. (2002). Network ties, reputation, and the financing of new ventures. *Management science*, *48*(3), 364–381.

Simon, H. A. (1955). A behavioral model of rational choice. *The quarterly journal of economics*, *69*(1), 99–118.

Spence, M. (2002). Signaling in retrospect and the informational structure of markets. *American Economic Review*, *92*(3), 434–459.

Stiglitz, J., & Weiss, A. (1983). Alternative approaches to analyzing markets with asymmetric information: Reply. *The American Economic Review*, *73*(1), 246–249.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American economic review*, *71*(3), 393–410.

Street, D. J., Burgess, L., & Louviere, J. J. (2005). Quick and easy choice sets: Constructing optimal and nearly optimal stated choice experiments. *International journal of research in marketing*, *22*(4), 459–470.

Surowiecki, J. (2005). *The wisdom of crowds*. Anchor.

Thurstone, L. L. (1927). A law of comparative judgment. *Psychological review*, *34*(4), 273.

Traets, F., Sanchez, D. G., & Vandebroek, M. (2020). Generating optimal designs for discrete choice experiments in r: The idefix package. *Journal Of Statistical Software*, *96*, 1–41.

Train, K. E. (2003). *Discrete choice methods with simulation*. Cambridge University Press. https://doi.org/10.1017/CBO9780511753930

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *science*, *185*(4157), 1124–1131.

Vismara, S. (2016). Equity retention and social network theory in equity crowdfunding. *Small Business Economics*, *46*(4), 579–590.

Vismara, S. (2018). Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice*, *42*(3), 467–497.

Vulkan, N., Åstebro, T., & Sierra, M. F. (2016). Equity crowdfunding: A new phenomena. *Journal of Business Venturing Insights*, *5*, 37–49.

Wald, A., Holmesland, M., & Efrat, K. (2019). It is not all about money: Obtaining additional benefits through equity crowdfunding. *The Journal of Entrepreneurship*, *28*(2), 270–294.

Welch, I. (1992). Sequential sales, learning, and cascades. *The Journal of finance*, *47*(2), 695–732.

Part IV

Study three

Chapter 4

From intention to action in financing new ventures: a data mining approach to real data

"Now, this is not the end.
It is not even the beginning of the end.
But it is, perhaps, the end of the beginning."
[Winston Churchill]

Abstract

Equity crowdfunding (hereinafter ECF) has recently become a valid alternative for new ventures for obtaining external financing resources. In an asymmetric information framework, entrepreneurs are supposed to ease the decision-making process of investors by conveying quality signals about their business projects. Information cascades originate from various signaling sources and are eased by the digital nature of ECF platforms. The observational learning theory suggests that investors are able to learn pieces of information from the simple observation of other (presumably better-informed) parties. The aim of this study is to advance the knowledge on herding and information cascades in ECF by replicating the research questions of the previous study of this thesis on real-world data, following the theory of planned behaviour. The analysis is conducted through a data mining process, following a preliminary data scraping phase to collect data. In the end, an econometric approach tested the research hypotheses from both a static cross-sectional perspective and a panel-data perspective. To the best of my knowledge, it is the first study on ECF that tries to validate findings on willingness-to-invest obtained via an

experimental setting by testing the hypotheses also in real-world data. Moreover, values of the study come also from its multi-platform nature, from the nature of the datasets obtained applying a data mining approach to concluded ECF campaigns across the years and from the jointly analysis of both a cross-sectional and panel-data perspectives.

Keywords: *Equity crowdfunding, signaling theory, information cascade, herd behavior, data mining*

4.1 Introduction

Equity crowdfunding (hereinafter ECF) has recently become a valid alternative for new ventures for obtaining external financing resources. It originated from traditional crowdfunding schemes but consists of a more sophisticated process, similar to an Initial Public Offering. The issuer sets up a web-based fundraising campaign with the aim of raising capital via an equity offering to a wide range of investors on primary markets under the supervision of an ECF platform. The investors receive ownership shares in return for their contribution and take part in the venture risks with the shareholders, with the expectancy of long-term profits. As distinct from other forms of crowdfunding, ECF is a profit-based crowdfunding model (Belleflamme et al., 2013).

The ECF environment represents a typical situation of information asymmetry, in which entrepreneurs possess wider venture-specific information. The multitude of investors, instead, is heterogeneous and mainly represented by a crowd of unsophisticated small investors that lack investment expertise or finance-specific skills to correctly evaluate the investment projects. Entrepreneurs are supposed to ease their decision-making process by conveying quality signals about their business ideas. Nevertheless, signals can come from different sources other than entrepreneurs and together constitute an information cascade based on multiple levels. It remains up to the receivers to pick the appropriate signals conveyed and interpret them correctly.

Moreover, the signaling mechanism is eased by the digital finance environment (i.e. FinTech) in which ECF operates. Its digital nature, indeed, allows real-time updates and ease both information sharing and knowledge sharing thanks to the platform websites. Similarly, social media networks constitute a thriving ground to convey signals and to revise the information set. The observational learning theory suggests that investors are able to learn pieces of information from the simple observation of other (presumably better-informed) parties.

The aim of this study is to advance the knowledge on herding and information cascades in ECF by replicating the research questions of the previous study of this thesis on real-world data. Here we are moving from an experimental approach, where willingness-to-invest of prospective investors was tested within a laboratory setting, to real data collected from various ECF campaigns across the years. Following the theory of planned behaviour, the two studies are linked as they shift from the exploration of intentions towards real-world investment decisions.

The analysis is conducted through a data mining process, following a preliminary data scraping phase to collect data. In the end, an econometric approach tested the research hypotheses from both a static cross-sectional perspective and a panel-data perspective.

Findings indicate that unsophisticated crowd-investors are subject to herd behaviour and interpret positively and significantly signals received from the crowd. In particular, investors tend to act as "birds of a feather flock together" and early-bird investors have the capability of convincing late and undecided ones. However, an important consideration has to be made. Due to its significant and strong impact, this signaling mechanism might also be used for bad practices and induce moral hazard. Indeed, entrepreneurs themselves or platform owners might disseminate manipulated information. Therefore, crowd-investors should be aware of bad practices and possibly verify whether investments are confirmed or not, as well as try not to rely only on this source of information.

To the best of my knowledge, it is the first study on ECF that tries to validate findings on willingness-to-invest obtained via an experimental setting by testing the hypotheses also in real-world data. Moreover, values of the study come also from its multi-platform nature, from the nature of the datasets obtained applying a data mining approach to concluded ECF campaigns across the years and from the jointly analysis of both a cross-sectional and panel-data perspectives.

4.2 Theoretical background

Following the preceding study (*Tapping the crowd for equity and herd behavior*) of this thesis, the theoretical framework is based on signaling theory and observational learning theory in digital finance environments. Here we advance the knowledge because we move from an experimental approach, where we mainly explore intentions to ECF invest within a laboratory setting, towards real life ECF investments, analyzed across years in various platform. Data has been analyzed with an econometric approach.

In contexts of asymmetric information, signaling theory explains the behavior of two parties that possess different sets of information. The better-informed party emits quality signals to the less-informed party in order to alleviate the information asymmetry and induce a choice (Spence, 1973; Spence, 2002). The theory was first developed by Spence (1973). In his seminal article the model was initially applied to the job market, where employers are not able to observe intangible traits of job seekers and face an investment (hiring) under uncertainty. Employees can use/acquire education credentials to convey effective signals to reduce employers' information deficit. Since the seminal article, signaling theory has been extended to different fields in economics and business studies (Connelly et al., 2011), such as entrepreneurship, without varying the key elements. The procedure is typically based on three steps: (i) the information insider (signaler) conveys private or intangible information in her/his possession to alleviate information asymmetries, (ii) the information outsider (receiver) observes and interprets the signal and (iii) the receiver eventually makes a decision based on the signal and feedback is sent to the signaler (Connelly et al., 2011; Block et al., 2018).

The ECF environment represents a typical situation of information asymmetry, in which capital seekers (entrepreneurs) possess wider venture-specific information and are supposed to convey quality signals to the crowd of investors in order to attract financing (Ahlers et al., 2015; Courtney et al., 2017). ECF belongs to the FinTech environment (Blaseg et al., 2021) and as a digital finance mechanism, it allows real-time information updates and ease information sharing through the platforms' websites and access to social media networks.

The observational learning theory, also known as social learning theory (Bandura and Walters, 1977), predicts that individual tend to rely on the decision-making of better-informed parties, when facing imperfect information (Bikhchandani et al., 1992). Late investors are able to learn from the observation of the behavior of better-informed parties and thus downscale asymmetric information. This learning process first derived from psychological literature and has been subsequently applied to financial studies in the form of "information cascades" (Welch, 1992; Vismara, 2018). The investors' attitude to imitate the behavior of others is commonly known within social finance studies as herding or herd behavior (Scharfstein and Stein, 1990; Bikhchandani and Sharma, 2000).

4.2.1 Research questions and research hypotheses

The research design applies the signaling theory and social learning theory to the ECF environment, where investors have access to a wide set of information about the campaigns, the new ventures, including financial measures and other firm-specific information, the entrepreneurs and team management, their social media network, the crowd of investors and the investment bids. Based on the theoretical framework, the study aims to answer the following research questions:

> *RQ1: What are the signals effectively learnt by prospective crowd-investors, among those disseminated through an information cascade, that can affect the likelihood of success of ECF campaigns?*
>
> *RQ2: Which signals disseminated and learnt through an information cascade might induce a herd behaviour among crowd-investors and, consequently, impact on the performance of ECF campaigns over time?*

Based on the research questions, the hypotheses are specified to be as follows.

Equity retention and entrepreneurs' skin-in-the-game.

The first signal is conveyed by the entrepreneurs themselves, who know better the real quality of her/his project. Entrepreneurs, as information insiders, are able to convey signals about their own commitment and self-confidence in their business ideas, thus revealing their skin-in-the-game (Frid et al., 2015). Therefore, entrepreneurs' willingness to invest and bear the risks of their own project signals good project quality (Leland and Pyle, 1977) and is revealed by the share of equity offered to investors. The percentage of equity shares offered to external stakeholders, or similarly, the percentage of equity shares retained by the entrepreneur(s), are clearly visible pieces of information on ECF campaigns. Indeed, prospective crowd-investors, in general, attempt to reduce information asymmetries by picking projects where entrepreneurs have made a significant, personal financial stake, and retained a higher proportion of equity (Vismara, 2016; Löher et al., 2018). This argument leads to Hypothesis 1:

> ***H1:*** *A larger proportion of equity retained by entrepreneurs increases the likelihood of ECF campaign success.*

Pre-money and business evaluation

Literature suggests that investors in ECF, in contrast to non-equity-based crowdfunding, are financially motivated and pay attention to information about business potentials (Löher et al., 2018). The pre-money valuation provides an estimate of the value of the new venture before raising ECF financing. The information is reported by the entrepreneur her/himself on the campaign webpage, but it is evaluated by experts such as advisors or analysts who have access to a wider set of information and skills than investors; they can also possibly observe softer pieces of information about the entrepreneurial team and entrepreneurs themselves, as they cooperate with them to aggregate useful information in order to produce an objective pre-money valuation.

In line with literature on financially motivated financing behaviour, crowd-investors attempt to reduce information asymmetries by picking projects with higher valuations as signals of good quality of the business conveyed by better-informed parties (Löher et al., 2018). This argument leads to Hypothesis 2:

> ***H2:*** *A higher pre-money valuation increases the likelihood of ECF campaign success.*

Investment behaviour of experts

The investment behaviour of experts is a publicly available source of information about business potentials. The presence of professional investors reveals that more sophisticated investors or qualified investors (e.g., BAs, VCs) with financial capabilities and expertise and/or investment institutions believe in the projects and supports it, often with larger bids. Their presence is seen as a good quality signal by crowd-investors, who presume that professional investors have access to wider information sets. At the same time, the presence of qualified investors extends beyond financial aspects, as they provide a wider set of value-added services to the new venture (Signori and Vismara, 2018). Thus, the investments made by qualified investors attracts late investors by both acting as a certification effect on business potential and reflecting a positive outlook. This argument leads to Hypothesis 3:

> ***H3:*** *The presence of professional investors increases the likelihood of ECF campaign success.*

Financial engagement

In an ECF framework, late crowd-investors can observe the bids made by early investors. Indeed, platforms transparently show the number, amount, proportion, frequency and timing of bids made by both unqualified and qualified investors. Previous literature has shown that early investments can effectively increase the likelihood of success by attracting late crowd-investors via information cascades (Vismara, 2018; Hornuf and Schwienbacher, 2018). A precise and easily understandable indicator of the early bids made is the percentage of target amount raised. It relates the capital raised to the minimum funding goal and signals the completion progress of the campaign. Eventually, the percentage raised represents a weighted measure of the financial engagement of external shareholders. Late bidders are more prone to invest in a project that is about to conclude successfully (Scharfstein and Stein, 1990). This argument leads to Hypothesis 4:

> ***H4:*** *A higher percentage of funding increases late crowd-investors' participation.*

Investment behaviour of peers and wisdom-of-the-crowd

Similarly, the platforms transparently show the investment behaviour of other crowd-investors. It could represent an effective signal that can be utilized as additional source of information to evaluate the quality of ECF campaigns, and thus business potential (Löher et al., 2018; Kleinert and Volkmann, 2019). The information set of peers is not believed to be wider than professional investors or advisors/analysts or entrepreneurs themselves and is collocated in a lower position in the information cascade hierarchy. However, it is believed that the wisdom of the crowd, collectively, can outperform the expertise and capabilities of individual experts (Surowiecki, 2005), as a signal regarding the good outlook of the investment (Block et al., 2018). Therefore, prospective crowd-investors engage in active observational learning (rational herding) from peers (Zhang and Liu, 2012). This argument leads to Hypothesis 5:

> ***H5:*** *A higher number of crowd-investors increases the likelihood of ECF campaign success.*

Information hubs and social media dimension

A less informative but still effective level of information cascade is represented by the social capital of entrepreneurs, expressed in terms of social media network. Following previous studies, the online presence of entrepreneurs acts as an endorsement of project quality (Vismara, 2016; Barbi and Mattioli, 2019). Indeed, social media provide access to project updates and discussions and enable interactions between investors and founders. In a digital finance context, as is ECF, social media play a crucial role as information hubs by easing information cascades and knowledge sharing (Vrontis et al., 2020). Thus, crowd-investors have the opportunity to downscale information asymmetries and validate less credible information. This argument leads to Hypothesis 6:

> ***H6:*** *The presence of entrepreneurs/new ventures on social media networks increases the likelihood of ECF campaign success.*

Geographical proximity and home bias

Following previous studies, crowd-investors prefer to invest locally (Agrawal et al., 2015), as they are more familiar with the country and the market in which the new venture is going to compete, recalling familiarity and home biases. Indeed, geographical proximity reduces screening costs, improve project selection, and ease due diligence and monitoring processes (Vrontis et al., 2020). Moreover, according to the cultural dimensions' theory (Hofstede, 2011), differences in culture across countries affect the values and behaviours of their members. This argument leads to Hypothesis 7:

> ***H7:*** *Domestic ventures are more likely to conclude successfully ECF campaigns.*

4.3 Data collection

Data is collected directly from the websites of several ECF platforms of different nationality through data mining processes in the period that goes from May 2019 until October 2020. The procedure consists of four main phases: (i) data scraping, (ii) data wrangling, (iii) data pre-processing and (iv) data analysis. Two identical processes, but at different frequencies of data extraction, are carried out to generate distinct datasets. The first one was run on a monthly basis from May 2019 until July 2020 and produced a cross-section dataset of concluded ECF campaigns. The second process was run on a weekly basis from August 2020 until October 2020 and produced a panel dataset of ECF campaigns with time-varying effects. Finally, we constructed an augmented dataset by hand-collecting some data (Hornuf and Schwienbacher, 2018), whenever possible, to integrate missing data left from scraping algorithms.

4.3.1 Data scraping

The first phase of a data mining process is the data retrieval, which consists of the actual gathering of raw data. Data retrieval is conducted via data scraping of publicly available information about ECF campaigns on the websites of platforms. Web data scraping is an automated procedure that simulates the human browsing of the World Wide Web via the Hypertext Transfer Protocol (HTTP) and recognizes the webpage structure to extract the raw data via selectors. In a nutshell, the web scraping procedure can be in turn synthetized into three sub-phases: (i) creation of a sitemap, (ii) configuration of selectors and selector tree (see Fig. 4.1), (iii) running the scraping algorithm. The

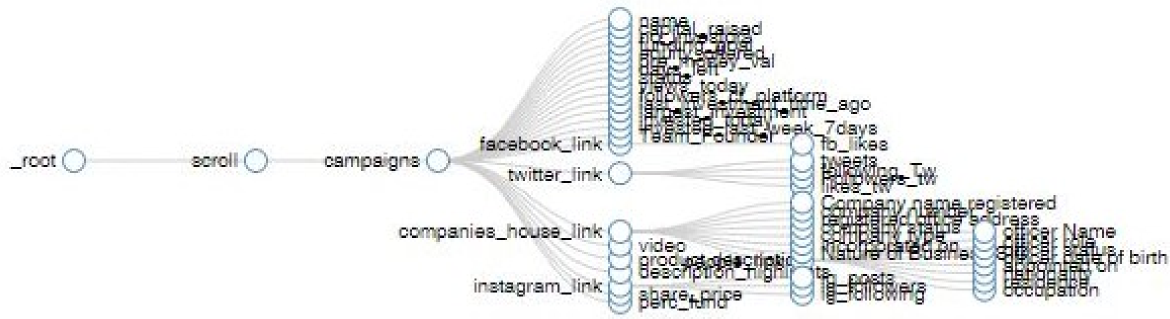


Figure 4.1: Example of a selector tree

procedure was conducted via *Webscraper.io* that is a Latvian browser extension. The automated scraping procedure on a regular basis assured that full data about the whole set of campaigns is collected, as some ECF platforms take investment decisions and information about the campaign off their website as soon as the funding limit is reached or the campaign closes, and some others do not retain any record about unsuccessful ventures (e.g. Crowdcube). Figure 4.2 shows an application of the Webscraper algorithm to extract data via a text selector.

4.3.2 Data wrangling and data preprocessing

Information retrieved from webpages consists of raw data that need to be transformed and processed in order to be analyzed and deposited in a usable dataset (Endel and Piringer, 2015). The whole process is divided into two phases, namely data wrangling and data preprocessing, and accounts for about 80% of time resources in a data mining process (Kandel et al., 2011). It consists of six basic steps: (i) discovering and understanding the raw data, (ii) organizing and merging the data, (iii) structuring the unstructured data,

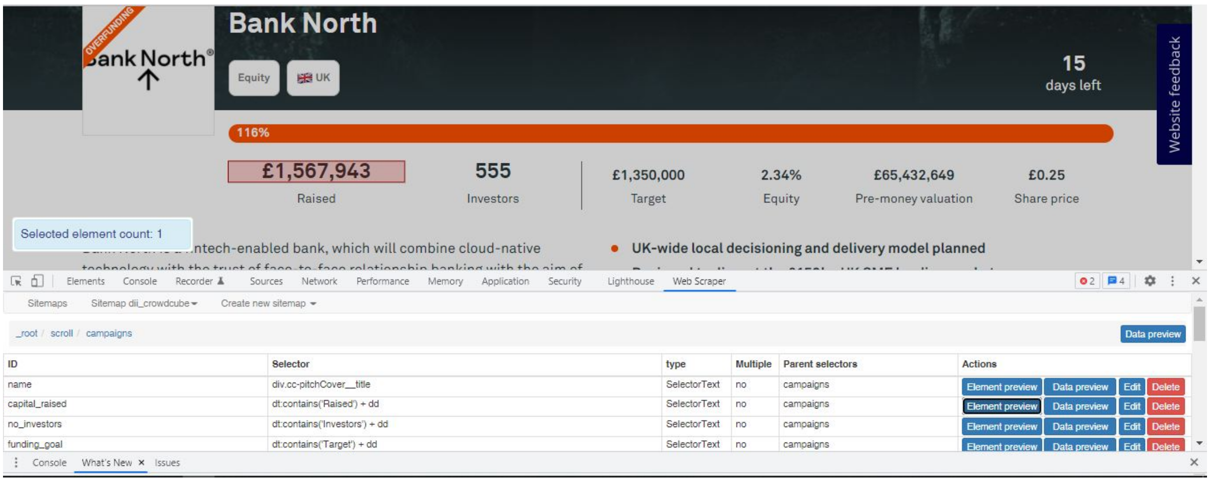


Figure 4.2: Example of an application of the webscraper algorithm

(iv) cleaning the data, (v) enriching the dataset with additional data, (vi) transforming the dataset.

The steps from (i) to (iv) pertain to the data wrangling phase and refers mainly to the organization and cleaning (e.g. conversion of decimal separator, conversion of the SI prefix K for thousand units, suppression of any characters classified as white space between numerical digits, as for *CHAR(160)*, etc.) of the raw dataset. Steps (v) and (vi) pertain to the data preprocessing phase and refers to the set of operations of manipulation and transformation of the wrangled dataset to enhance the performance (Alasadi and Bhaya, 2017). In particular, the main preprocessing operations consisted of generation and transformation of variables, variables conversion, variables destringing, data smoothing, data integration, currency conversion (at the exchange rate to date of extraction), normalization and data reduction. Some missing data has been integrated via the scraping of web pages other than the ECF platforms such as the UK governmental Companies House, the social media profiles of the new ventures and nascent entrepreneurs and other ECF data sources (NextFin, Findcrowdfunding, Crunchbase). In some cases, the hand-collection of missing data was necessary whenever the Webscraper algorithm was not able to retrieve correctly the data.

Data wrangling and data preprocessing are mainly conducted via the software STATA SE 15 and regular expressions and macros applied to the spreadsheets.

4.4 Description of the samples

4.4.1 Platforms' description

Data is retrieved investigating regularly and automatedly the websites of a set of ten ECF platforms of different nationalities in order to seize cross-cultural effects and increase the dimensionality of the sample. Moreover, the use of multi-platform studies reduces the risk of selection bias (Dushnitsky and Fitza, 2018) and increase the generalisability of our results. The exploratory analysis of these ten platforms serves not only to provide descriptive statistics about the phenomenon from a cross-cultural-cross-platform perspective, but are also deployed in the classification analysis (see sections "Machine learning" and "Classification") in order to gather a preliminary survey of the set of features identified with labelled successful campaigns. However, the subsequent empirical settings (Panel A and Panel B) are built upon a narrower number of platforms due to information disclosure limitations and heterogeneity across platforms. In particular, Panel A considers up to three platforms (i.e. Crowdcube, Mamacrowd and 200Crowd), as well as does Panel B (i.e. Crowdcube, Seedrs and Invesdor).

The platforms are described presently[1]. For each platform is also offered a table containing descriptive statistics from real-world data collected via data scraping (Tab 4.1 - Tab 4.10).

200crowd

"Two Hundred crowd" (200crowd) is an Italian-based ECF platform located in Milan. It was founded in 2017 after a successful ECF round of 300,000€ raised on the Tip Ventures portal (former owner and brand name of the portal, active since 2015). It is recognized and authorized by the Italian Companies and Exchange Commission (CONSOB) and operates following the "all-or-nothing" scheme (Cumming et al., 2020), with an extended time period provided in case of overfunding. The new brand name, according to Matteo Masserdotti (CEO and Founder of 200crowd), derives from the IT, where the "HTTP 200 OK" success status response code indicates that the server request has succeeded. It is the first Italian ECF platform that uses the syndication investment model, in which

[1]Information about the platforms is based on examination of the following platform websites and their relative social media (as of end January 2022): www.200crowd.com, www.companisto.com, www.crowdcube.com, www.crowdfunder.com, www.fundedbyme.com, www.invesdor.com, www.mamacrowd.com, www.opstart.it, www.seedrs.com, and www.sowefund.com.

investors acquires convertible shares of special purpose vehicles (SPV; i.e. Business angels or venture capitalists) instead of shares of the new venture. The first syndicate ECF campaign was launched in June 2018 for the startup "Checkout technologies" promoted by Pariter Partners (a group of Business Angels).

	Obs.	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
Capital raised in EUR	48	292828.85	150500.00	504261.23	1000.00	3295500
Capital raised (log)	48	11.86	11.92	1.33	6.91	15
Campaign success	48	0.77	1.00	0.42	0.00	1
Equity retention	48	90.20	92.26	6.24	75.00	98
Pre-money valuation	48	3759300.85	2000000.00	6358875.43	450000.00	43478261
Pre-money valuation (log)	48	14.65	14.51	0.87	13.02	18
Presence of professional investors	48	0.77	1.00	0.42	0.00	1
Percentage of capital raised	48	1.62	1.49	1.11	0.00	4
Number of investors	48	66.35	30.00	152.19	2.00	1060
No. social media	0	.	.	.	.	.
Presence on social media	0	.	.	.	.	.
Geographical proximity	0	.	.	.	.	.
Covid period	48	0.15	0.00	0.36	0.00	1
Minimum investment target	48	171875.00	120000.00	163165.58	50000.00	1000000
Log min funding goal	48	11.79	11.70	0.68	10.82	14
Maximum investment target	48	437270.83	300000.00	508535.94	100000.00	3500000
Log max funding goal	48	12.70	12.61	0.69	11.51	15
Entrepreneur gender	0	.	.	.	.	.
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	0	.	.	.	.	.
Equity	0	.	.	.	.	.
Largest investment	0	.	.	.	.	.
Interested investors	48	42.06	23.00	103.99	1.00	729
Presence on Facebook	0	.	.	.	.	.
Presence on Twitter	0	.	.	.	.	.
Presence on LinkedIn	0	.	.	.	.	.
Presence on Instagram	0	.	.	.	.	.
Observations	48					

Table 4.1: Descriptive statistics for 200crowd

Companisto

Companisto is a German-based ECF platform located in Berlin. It was founded in 2012 by the lawyers David Rhotert and Tamo Zwinge and follows a traditional "all-or-nothing" ECF investment scheme in which investors become shareholders and are entitled to a share of any profits, as well as potentially benefiting from an exit (Hobey, 2015), only in the case in which the minimum funding amount is reached. It is authorized by the German Trade, Commerce and Industry Regulation Act (Gewerbeordnung) and supervised by the BA Friedrichshain-Kreuzberg von Berlin Ordnungs- und Gewerbeamt authority. It is currently the largest equity-investment network for startups and SMEs in Germany as it allowed 202 successful financing rounds for an amount of 134 million € (as of January 2022).

	Obs.	Mean	Median	Std. Dev	Min	Max
Capital raised in EUR	110	553338.13	300000.00	757675.55	31080.00	5000000
Capital raised (log)	110	12.65	12.61	1.06	10.34	15
Campaign success	0	.	.	.	.	.
Equity retention	0	.	.	.	.	.
Pre-money valuation	0	.	.	.	.	.
Pre-money valuation (log)	0	.	.	.	.	.
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	0	.	.	.	.	.
Number of investors	101	677.86	627.00	396.95	47.00	2276
No. social media	0	.	.	.	.	.
Presence on social media	0	.	.	.	.	.
Geographical proximity	0	.	.	.	.	.
Covid period	111	0.16	0.00	0.37	0.00	1
Minimum investment target	0	.	.	.	.	.
Log min funding goal	0	.	.	.	.	.
Maximum investment target	0	.	.	.	.	.
Log max funding goal	0	.	.	.	.	.
Entrepreneur gender	0	.	.	.	.	.
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	107	685.10	480.00	867.02	120.00	5141
Equity	0	.	.	.	.	.
Largest investment	0	.	.	.	.	.
Interested investors	0	.	.	.	.	.
Presence on Facebook	0	.	.	.	.	.
Presence on Twitter	0	.	.	.	.	.
Presence on LinkedIn	0	.	.	.	.	.
Presence on Instagram	0	.	.	.	.	.
Observations	111					

Table 4.2: Descriptive statistics for Companisto

Crowdcube

Crowdcube is located in Exeter, UK and is the largest British ECF platform with about £1 billion successfully raised from a crowd of 1.2 million backers (as of January 2022; AltFi, 2022). It was founded in 2011 by Darren Westlake and Luke Lang. The platform works in a traditional "all-or-nothing" ECF-investment scheme and offers a marketplace not only for equity shares, but also for mini-bonds since 2014. It charges a 7% fee of the amount raised to the founders and in 2018 introduced a 1.5% investor fee (capped at £250) in case of successful collection of the capital. The platform provides consulting services to new ventures in developing business pitches, financial forecasts, and principal agency between investors and company. Due to the high number of campaigns published frequently, the platform takes off information about unsuccessful campaigns the website and here lies the advantage of adopting a data scraping approach. Moreover, the platform provide access to the Companies House's website, which is the UK company register, where firms file specific details about their business as required by legislation. Crowdcube is authorized to operate in UK by the Financial Conduct Authority since 2013 and is regulated by the Financial Services Authority.

	Obs.	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
Capital raised in EUR	312	583970.98	238127.50	1090904.73	19630.00	11340210
Capital raised (log)	312	12.51	12.38	1.17	9.88	16
Campaign success	314	0.73	1.00	0.45	0.00	1
Equity retention	307	91.13	92.09	4.73	73.14	98
Pre-money valuation	303	8027287.49	3000000.00	20385843.60	333333.00	251000000
Pre-money valuation (log)	303	15.07	14.91	1.12	12.72	19
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	314	1.59	1.28	1.30	0.20	10
Number of investors	314	490.05	273.00	857.62	27.00	10363
No. social media	314	0.35	0.00	0.48	0.00	1
Presence on social media	314	0.36	0.00	0.48	0.00	1
Geographical proximity	313	0.83	1.00	0.37	0.00	1
Covid period	314	0.19	0.00	0.39	0.00	1
Minimum investment target	312	338642.76	200000.00	399539.92	10000.00	4000000
Log min funding goal	312	12.30	12.21	0.91	9.21	15
Maximum investment target	0	.	.	.	.	.
Log max funding goal	0	.	.	.	.	.
Entrepreneur gender	312	0.22	0.00	0.42	0.00	1
Entrepreneur age	309	45.29	45.00	11.09	23.00	76
Entrepreneur seniority	312	3.68	3.00	2.77	0.00	17
Firm age	313	4.65	4.00	3.23	0.00	22
Price per share	10	2.59	1.24	2.90	0.13	9
Equity	0	.	.	.	.	.
Largest investment	52	323614.83	50000.00	1458230.82	5012.00	10500000
Interested investors	224	1127.59	677.50	1540.53	19.00	16836
Presence on Facebook	0	.	.	.	.	.
Presence on Twitter	314	0.09	0.00	0.29	0.00	1
Presence on LinkedIn	0	.	.	.	.	.
Presence on Instagram	314	0.26	0.00	0.44	0.00	1
Observations	314					

Table 4.3: Descriptive statistics for Crowdcube

Crowdfunder.com

Crowdfunder.com was a US-based ECF platform located in Los Angeles. It was founded in 2012 and is currently not active since September 2020. The platform offered a marketplace for both "Keep-it-all" ECF-based investments schemes and for syndication investments with a VC owned by the platform (VC Index Fund). The "keep-it-all" scheme allows the new ventures to keep all the capital raised at the end of a campaign regardless of whether or not the minimum funding goal is reached. The platform allowed for accredited investors only and asked a monthly fee based on different subscription packages (Starter, Premium, Premium Plus) for the use of its platform to both investors and entrepreneurs. However, apart from the subscription fee to list the campaign, Crowdfunder did not charge any additional fee on the amount raised. Due diligence on new ventures was not performed by the platform, but it was investors' responsibility. Data was retrieved until July 2020, and apparently the platform shut down a few months later.

	Obs.	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
Capital raised in EUR	134	776859.56	54600.00	1810653.02	0.00	10117800
Capital raised (log)	134	8.31	10.90	5.98	0.00	16
Campaign success	134	0.13	0.00	0.33	0.00	1
Equity retention	0	.	.	.	.	.
Pre-money valuation	0	.	.	.	.	.
Pre-money valuation (log)	0	.	.	.	.	.
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	134	0.52	0.05	1.52	0.00	15
Number of investors	0	.	.	.	.	.
No. social media	288	0.57	0.00	0.82	0.00	3
Presence on social media	288	0.38	0.00	0.48	0.00	1
Geographical proximity	287	0.84	1.00	0.37	0.00	1
Covid period	288	0.16	0.00	0.36	0.00	1
Minimum investment target	134	2180978.51	907200.00	3176186.19	1680.00	21000000
Log min funding goal	134	13.76	13.72	1.45	7.43	17
Maximum investment target	0	.	.	.	.	.
Log max funding goal	0	.	.	.	.	.
Entrepreneur gender	264	0.13	0.00	0.34	0.00	1
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	127	8626.25	4200.00	10128.60	8.40	42000
Equity	0	.	.	.	.	.
Largest investment	0	.	.	.	.	.
Interested investors	0	.	.	.	.	.
Presence on Facebook	288	0.24	0.00	0.43	0.00	1
Presence on Twitter	288	0.26	0.00	0.44	0.00	1
Presence on LinkedIn	288	0.07	0.00	0.26	0.00	1
Presence on Instagram	0	.	.	.	.	.
Observations	288					

Table 4.4: Descriptive statistics for Crowdfunder

Fundedbyme

Fundedbyme is a Swedish platform based in Stockholm and operating in Finland, Poland, Malaysia, The Netherlands, Singapore and The United Arab Emirates via joint ventures.

It was founded by Arno Smit and Daniel Daboczy in 2011 as a CF-based platform before switching to ECF in 2012, following an "All-or-nothing" scheme. The platform applies a 1.9% fee on capital invested. Fundedbyme got listed at the NGM Nordic MTF stock market in 2019. As of 2022 the platform raised about €74 million from a crowd of 250,000 backers.

	Obs.	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
Capital raised in EUR	197	242205.29	126004.48	324465.57	5462.23	2067927
Capital raised (log)	197	11.80	11.74	1.10	8.61	15
Campaign success	36	1.00	1.00	0.00	1.00	1
Equity retention	195	90.79	92.88	8.17	25.07	99
Pre-money valuation	0	.	.	.	.	.
Pre-money valuation (log)	0	.	.	.	.	.
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	0	.	.	.	.	.
Number of investors	3	54.67	39.00	28.01	38.00	87
No. social media	213	0.91	1.00	0.58	0.00	2
Presence on social media	213	0.78	1.00	0.41	0.00	1
Geographical proximity	213	0.74	1.00	0.44	0.00	1
Covid period	213	0.17	0.00	0.38	0.00	1
Minimum investment target	3	206663.40	97990.20	256862.61	22000.00	500000
Log min funding goal	3	11.54	11.49	1.56	10.00	13
Maximum investment target	1	515278.50	515278.50	.	515278.50	515279
Log max funding goal	1	13.15	13.15	.	13.15	13
Entrepreneur gender	0	.	.	.	.	.
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	1	102.90	102.90	.	102.90	103
Equity	0	.	.	.	.	.
Largest investment	0	.	.	.	.	.
Interested investors	39	50.82	25.00	57.08	4.00	245
Presence on Facebook	213	0.77	1.00	0.42	0.00	1
Presence on Twitter	0	.	.	.	.	.
Presence on LinkedIn	0	.	.	.	.	.
Presence on Instagram	213	0.14	0.00	0.35	0.00	1
Observations	213					

Table 4.5: Descriptive statistics for FundedByMe

Invesdor

Invesdor is located in Helsinki, Finland, and is the first ECF-based platform operating in northern Europe. It was founded in 2012 by Lasse Mäkelä (CEO), Miikka Poutiainen, Petteri Poutiainen, Timo Lappi, Jouni Leskinen and Lare Lekman and in 2015 became the first European ECF platform to obtain MiFID II license by financial authorities to expand debt and ECF services across all 31 EU and EEA countries. In 2019 Invesdor merged with Nordic and Finnest to form the Invesdor Group Ltd. The platform operates through an "all-or-nothing" model and is supervised by the Finnish Financial Supervisory Authority. As of January 2022, it has collected about €160 million.

	Obs.	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
Capital raised in EUR	140	520297.60	281581.00	608932.40	11130.00	3634663
Capital raised (log)	140	12.53	12.55	1.21	9.32	15
Campaign success	146	0.86	1.00	0.35	0.00	1
Equity retention	1	77.82	77.82	.	77.82	78
Pre-money valuation	7	2889017.78	2806624.00	807762.25	1987828.00	4046800
Pre-money valuation (log)	7	14.84	14.85	0.29	14.50	15
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	146	1.78	1.46	1.33	0.14	10
Number of investors	4	355.75	354.00	281.94	27.00	688
No. social media	153	0.62	1.00	0.49	0.00	1
Presence on social media	153	0.63	1.00	0.49	0.00	1
Geographical proximity	153	0.86	1.00	0.35	0.00	1
Covid period	153	0.22	0.00	0.42	0.00	1
Minimum investment target	146	292371.67	200000.00	276154.04	20000.00	1500000
Log min funding goal	146	12.12	12.21	1.04	9.90	14
Maximum investment target	0	.	.	.	.	.
Log max funding goal	0	.	.	.	.	.
Entrepreneur gender	121	0.19	0.00	0.39	0.00	1
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	2	149.50	149.50	0.71	149.00	150
Equity	0	.	.	.	.	.
Largest investment	0	.	.	.	.	.
Interested investors	0	.	.	.	.	.
Presence on Facebook	0	.	.	.	.	.
Presence on Twitter	0	.	.	.	.	.
Presence on LinkedIn	153	0.62	1.00	0.49	0.00	1
Presence on Instagram	0	.	.	.	.	.
Observations	153					

Table 4.6: Descriptive statistics for Invesdor

Mamacrowd

Mamacrowd is the leading Italian ECF-based platform and is located in Milan. It was founded in 2011 by SiamoSoci and is currently managed by the same company. It is recognized and authorized by the Italian Companies and Exchange Commission (CONSOB) since 2014. The platform does not charge any fee for the use of the portal and operates following the "all-or-nothing" model. In 2022 the asset management operator Azimut acquired the majority stake in Mamacrowd. As of January 2022, the platform raised about €100 million.

	Obs.	Mean	Median	Std. Dev	Min	Max
Capital raised in EUR	97	178604.51	332.25	452651.38	0.00	2670161
Capital raised (log)	97	7.15	5.81	3.82	0.00	15
Campaign success	97	0.85	1.00	0.36	0.00	1
Equity retention	97	90.75	94.59	15.27	2.00	99
Pre-money valuation	97	3276354.34	2100000.00	2982567.83	1000.00	14000000
Pre-money valuation (log)	97	14.52	14.56	1.37	6.91	16
Presence of professional investors	97	0.85	1.00	0.36	0.00	1
Percentage of capital raised	97	2.20	1.83	1.71	0.00	10
Number of investors	97	122.38	72.00	226.78	0.00	2080
No. social media	97	2.10	2.00	1.06	0.00	4
Presence on social media	97	0.91	1.00	0.29	0.00	1
Geographical proximity	97	1.00	1.00	0.00	1.00	1
Covid period	97	0.12	0.00	0.33	0.00	1
Minimum investment target	97	187712.07	149996.00	145915.22	6006.00	650000
Log min funding goal	97	11.88	11.92	0.74	8.70	13
Maximum investment target	97	652868.10	428000.00	893311.62	100000.00	8000000
Log max funding goal	97	13.03	12.97	0.76	11.51	16
Entrepreneur gender	97	0.11	0.00	0.32	0.00	1
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	97	820.78	499.74	2090.24	100.00	19999
Equity	97	100194.10	11111.11	530247.43	100.00	5159866
Largest investment	0	.	.	.	.	.
Interested investors	0	.	.	.	.	.
Presence on Facebook	97	0.60	1.00	0.49	0.00	1
Presence on Twitter	97	0.53	1.00	0.50	0.00	1
Presence on LinkedIn	97	0.87	1.00	0.34	0.00	1
Presence on Instagram	97	0.11	0.00	0.32	0.00	1
Observations	97					

Table 4.7: Descriptive statistics for Mamacrowd

Opstart

Opstart is an Italian ECF platform located in Bergamo and founded in 2015. It is recognized and authorized by the Italian Companies and Exchange Commission (CONSOB) and operates following an "all-or-nothing" scheme. In 2020, during the Covid-19 pandemic, Opstart qualified as the first Italian ECF platform in raising capital.

Seedrs

Seedrs is a British ECF platform located in London and operating also in Lisbon, Portugal. It was originally conceived by Jeff Lynn and Carlos Silva in 2009 as a reward-based CF platform. In 2012 it switched to the ECF model and obtained the authorization to operate in UK by the Financial Conduct Authority, following an "all-or-nothing" scheme. In June 2017 Seedrs became the first ECF platform to launch a (beta) secondary market for allowing crowd-investors to buy and sell shares in unlisted companies. According

	Obs.	Mean	Median	Std. Dev	Min	Max
Capital raised in EUR	80	294869.90	127375.00	755406.37	3000.00	6120000
Capital raised (log)	80	11.69	11.75	1.24	8.01	16
Campaign success	80	0.85	1.00	0.36	0.00	1
Equity retention	0	.	.	.	.	.
Pre-money valuation	80	1712726.22	1140000.00	1943782.39	10000.00	13502000
Pre-money valuation (log)	80	13.87	13.95	1.15	9.21	16
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	80	4.93	1.51	21.87	0.02	195
Number of investors	0	.	.	.	.	.
No. social media	80	0.63	1.00	0.66	0.00	3
Presence on social media	80	0.54	1.00	0.50	0.00	1
Geographical proximity	0	.	.	.	.	.
Covid period	80	0.21	0.00	0.41	0.00	1
Minimum investment target	80	105672.95	75000.00	112086.65	500.00	750000
Log min funding goal	80	11.21	11.23	0.99	6.22	14
Maximum investment target	80	447907.33	202750.00	985418.86	30000.00	8000000
Log max funding goal	80	12.37	12.22	0.96	10.31	16
Entrepreneur gender	80	0.07	0.00	0.27	0.00	1
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	79	2121.86	250.00	7246.39	100.00	50000
Equity	0	.	.	.	.	.
Largest investment	0	.	.	.	.	.
Interested investors	0	.	.	.	.	.
Presence on Facebook	80	0.51	1.00	0.50	0.00	1
Presence on Twitter	80	0.07	0.00	0.27	0.00	1
Presence on LinkedIn	0	.	.	.	.	.
Presence on Instagram	80	0.04	0.00	0.19	0.00	1
Observations	80					

Table 4.8: Descriptive statistics for Opstart

to AltFi (2021), Seedrs is the second largest platform in the UK, with a funded equity volume of £130 million as of Q2 2021. In Q1 2021, a merger deal between Seedrs and Crowdcube failed due competition concerns raised by the FCA, but the platform was then acquired by the US FinTech Republic in December 2021.

Sowefund

Sowefund is a French ECF-based platform located in Paris. It was founded in 2014 by a team of innovation financing and capital investment professionals and is regulated by the Autorité des Marchés Financiers (AMF) as a recognized Conseiller en Investissements Participatifs (CIP). The platform charges between 6% and 10% of the total amount of the fundraising to the new ventures and 1.5% fee to investors for each payment. As of January 2022, Sowefund raised about €55 million.

	Obs.	Mean	Median	Std. Dev	Min	Max
Capital raised in EUR	748	965530.23	314472.38	1829876.58	910.56	17299922
Capital raised (log)	748	12.77	12.66	1.48	6.82	17
Campaign success	741	0.87	1.00	0.34	0.00	1
Equity retention	610	90.43	91.67	6.11	60.00	100
Pre-money valuation	12	12102739.83	5985049.50	16976683.43	2248253.00	64101280
Pre-money valuation (log)	12	15.81	15.60	0.94	14.63	18
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	741	1.34	1.15	0.70	0.00	9
Number of investors	132	378.02	266.00	324.57	38.00	1624
No. social media	769	0.39	0.00	0.53	0.00	3
Presence on social media	769	0.37	0.00	0.48	0.00	1
Geographical proximity	273	0.87	1.00	0.34	0.00	1
Covid period	769	0.16	0.00	0.37	0.00	1
Minimum investment target	675	513779.19	224014.56	897961.95	770.56	11119481
Log min funding goal	675	12.33	12.32	1.37	6.65	16
Maximum investment target	0	.	.	.	.	.
Log max funding goal	0	.	.	.	.	.
Entrepreneur gender	1	0.00	0.00	.	0.00	0
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	423	84.20	8.40	1063.83	0.01	21500
Equity	0	.	.	.	.	.
Largest investment	10	648124.50	226475.00	1248194.62	25780.00	4163030
Interested investors	10	839.80	889.00	499.73	135.00	1595
Presence on Facebook	769	0.03	0.00	0.16	0.00	1
Presence on Twitter	769	0.21	0.00	0.41	0.00	1
Presence on LinkedIn	769	0.14	0.00	0.35	0.00	1
Presence on Instagram	769	0.01	0.00	0.10	0.00	1
Observations	769					

Table 4.9: Descriptive statistics for Seedrs

4.4.2 Cross-sectional dataset

The "static" or "cross-sectional" dataset is obtained by scraping information from ten platforms (200crowd, Companisto, Crowdcube, Crowdfunder, Fundedbyme, Invesdor, Mamacrowd, Opstart, Seedrs, Sowefund) and among 2,177 startups at a monthly frequency, for a total of thirteen periods, from May 2019 until July 2020. Due to its low frequency of scraping and due to the average length of a campaign, generally between thirty and sixty days, this dataset analyzes data of concluded campaigns without time-varying effects. Moreover, the dataset also includes information about campaigns concluded before the scraping, whenever available. The scraping algorithm extracted 54 variables/features in total.

	Obs.	Mean	Median	Std. Dev	Min	Max
Capital raised in EUR	13	0.00	0.00	0.00	0.00	0
Capital raised (log)	13	0.00	0.00	0.00	0.00	0
Campaign success	94	0.39	0.00	0.49	0.00	1
Equity retention	0	.	.	.	.	.
Pre-money valuation	0	.	.	.	.	.
Pre-money valuation (log)	0	.	.	.	.	.
Presence of professional investors	0	.	.	.	.	.
Percentage of capital raised	57	0.00	0.00	0.00	0.00	0
Number of investors	0	.	.	.	.	.
No. social media	0	.	.	.	.	.
Presence on social media	0	.	.	.	.	.
Geographical proximity	96	0.96	1.00	0.20	0.00	1
Covid period	104	0.13	0.00	0.34	0.00	1
Minimum investment target	97	480618.56	400000.00	798825.72	50000.00	8000000
Log min funding goal	97	12.79	12.90	0.67	10.82	16
Maximum investment target	81	450617.28	500000.00	165494.30	100000.00	800000
Log max funding goal	81	12.94	13.12	0.43	11.51	14
Entrepreneur gender	33	0.12	0.00	0.33	0.00	1
Entrepreneur age	0	.	.	.	.	.
Entrepreneur seniority	0	.	.	.	.	.
Firm age	0	.	.	.	.	.
Price per share	104	1033.65	100.00	5528.16	100.00	50000
Equity	0	.	.	.	.	.
Largest investment	0	.	.	.	.	.
Interested investors	0	.	.	.	.	.
Presence on Facebook	0	.	.	.	.	.
Presence on Twitter	0	.	.	.	.	.
Presence on LinkedIn	0	.	.	.	.	.
Presence on Instagram	0	.	.	.	.	.
Observations	104					

Table 4.10: Descriptive statistics for Sowefund

4.4.3 Panel datset

The “dynamic” or “longitudinal” dataset is obtained by scraping information from three platforms (Crowdcube, Invesdor, Seedrs) and among 737 startups at a weekly frequency, for a total of 12 periods, from August 2020 until October 2020. The increased frequency of data extraction allows to observe for time-varying effects and thus adopt (unbalanced) panel data econometric models. The time dimension of the panel data set is the duration of the campaign in weeks, while the cross-sectional dimension refers to the new ventures. The scraping algorithm extracted 46 variables/features in total.

4.4.4 Variables description

The present paragraph lists and describes the set of dependent and independent variables used in the empirical settings. Some of them are not commonly available for all the platforms and thus there are instances of missing values for certain observations and not all the models were able to use all the variables (as for Nitani et al., 2019). Variables expressed in monetary units are converted in Euro (preprocessing phase) at the exchange rate of the date of data extraction from several currencies adopted by the platforms (e.g. CHF, DKK, GBP, MYR, NOK, PLN, SEK, USD). Logarithmic transformations of monetary variables are used to analyze expected relative (percentage) changes on the coefficients, as well as to improve the fit of the models by reducing variables' skewness. Transformations are obtained during the preprocessing phase by applying the log function to the monetary values added to one starting unit (i.e. a positive constant; $log(1 + x)$), as the data contains zeros (Lukkarinen et al., 2016)

Dependent variables

In this empirical analysis, the success of an individual crowdfunding campaign is measured by two approaches, and thus we use two different dependent variables:

(1) *Capital raised:* measures the total amount of capital raised (in Euro) by the new venture during the campaign.

(2) *Funding success:* is a dichotomous variable that measures whether the pre-determined minimum funding goal has been reached (= 1) or not (= 0) within the fundraising period. In other words, it expresses whether the amount raised equals or exceeds the amount targeted. The variable is generated through regular expressions and took the value of 1 if the web scraper detected the label "financed" (e.g. "Financed", "Financé", "Finanziata", etc.) in the respective HTML section of the campaign's website, and/or if the ratio (automatedly calculated on the spreadsheets) between capital raised and minimum funding goal is equal or exceeding 1; the variable took the value of 0 otherwise, i.e. the campaign is labelled as "not financed" and/or the ratio is lower than 1, subject to the condition that data is not NA.

Independent variables

To investigate the RQs a specific set of variables of interest among those extracted is considered. The chosen explanatory variables are the following:

(1) *Equity retention:* measures the percentage of the firm's share retained by the entrepreneur(s) and represents their skin-in-the-game. It is generated as the complement to 100 of the percentage of shares offered, which represents the percentage of

firms' shares offered to future shareholders (in case of successful ECF campaign) and is a publicly available piece of information and can be retrieved from the campaign website.

(2) *Pre-money valuation:* measures the estimated value (in Euro) of the new venture before launching the ECF campaign, as evaluated by analysts/advisors and/or consultants.

(3) *Presence of professional investors:* signals whether a professional investor (e.g. financial intermediaries, venture capitalists, business angels, etc.) has bid and secured shares in the new ventures.

(4) *Percentage of funding:* measures the percentage of capital raised as the ratio between the total amount of capital raised and the minimum financing goal, recalling that the new venture will be financed on the condition that at least 100% of percentage of funding is reached, and captures the financial engagement of investors (retail and professional).

(5) *Number of investors:* measures the number of crowd-investors that have supported the campaign and captures the wisdom-of-the-crowd.

(6) *Online presence:* captures the presence of the firm/entrepreneur(s) on social media. The variable is generated as a dummy and takes on the value of 1 whether the new venture provided information (e.g. active URLs) to its social media accounts, i.e. at least one between LinkedIn, Twitter, Facebook and Instagram, or not (= 0) subject to the condition that the ECF platform provided a common HTML section on its website for this information.

(7) *Social media count:* reflects the usage of social media networks to promote the ECF campaign and the business idea by counting the number of direct links to social media web pages. It measures the quantity of social/alliance capital accessible from the campaign's page (Facebook, Twitter, Instagram, LinkedIn).

(8) *Geographical proximity:* measures whether the new venture's registered office is located in the same country of the ECF platform in which is listed. It represents the geographical and cultural proximity. It is a dummy variable generated by matching

the locations of the two parties that takes the value of 1 in case of positive matching and 0 otherwise.

Control variables

Along with the explanatory variables we included several control variables organized as clusters.

The first cluster consists of attributes of the ECF campaign:

- *Minimum funding goal:* the minimum target amount of capital (in Euro) to be raised to reach the funding goal (floor).

- *Maximum funding goal:* is the maximum amount of capital (in Euro) that could be raised (cap). It is set by the entrepreneurs to allow for overfunding and at the same time avoid excessive dilution of the control shares.

- *Days left:* measures the days left to the conclusion of the campaign (for the panel dataset only).

- *Covid period:* it is a dummy-generated variable (for the cross-sectional dataset only) that states whether the fundraising campaign was launched during the Covid-19 pandemic (=1; from March 2020) or earlier (=0).

- *Platform:* categorical-generated variable that controls for the platform on which the new venture is listed.

- *Country:* categorical-generated variable that controls for the Platform country on which the new venture is listed.

The second cluster consists of attributes of the financing round:

- *Largest investment:* measures the largest investment (in Euro) made by a single investor during the campaign.

- *Interested investors:* measures the number of potential investors that expressed interest in the campaign (through a click on the campaign's website) and follow its updates.

The third cluster consists of attributes of the firm and of financial measures derived from financial statements disclosed:

- *Firm maturity:* measures the age of the firm in years since its establishment.

- *Share price:* measures the price for a single ECF share of the firm; in other words it represents the minimum investment required to a single investor.

- *Equity:* measures the net balance of the firm's assets reduced by the liabilities.

The fourth cluster consists of attributes of the entrepreneurs/management team:

- *Gender:* is a dummy-generated variable reflecting the gender of the primary owner (= 1) if female, (= 0) if male. The variable is generated via a tool (Genderize.io) that estimates the gender from the name, surname and nationality of an individual within a certain confidence interval. Not-significant estimates were then revised by the author and hand-collected.

- *Entrepreneur age:* reflects the age of the entrepreneur in years.

- *Owner seniority:* represent the number of years in which the current owner has been performing the role of director within the same firm.

As anticipated before, it is worth pointing out that in the second and third empirical settings (i.e. Panel A and Panel B) the explanatory-variable sets are kept fixed in order to test the research hypotheses. However, the control-variable sets are going to differ among the platforms, as for Nitani et al. (2019). The main reason lies in the heterogeneity in information disclosure from the platform side. Indeed, each platform chooses to what extent being informative towards prominent investors and which pieces of information exhibit on campaigns' websites. As a result, some platforms turn out to possess/disclose more information (i.e. control variables to be extracted) than others. Lastly, it is worth considering that the following aggregate models (i.e. models that examine campaigns from several platforms) are built upon similar independent-variable sets, and thus excluding heterogeneous control variables.

4.5 Data analysis method

The data mining methodology allow to convert raw and unstructured data to knowledge, according to the Knowledge Discovery in Databases (KDD) process (Fayyad et al., 1996). After having retrieved, wrangled, preprocessed and transformed (see previous sections) the data, two steps are next: data analysis and interpretation/evaluation of the results. As for the former, the present research design encompasses three empirical analyses: (i) classification via machine learning, (ii) cross-sectional analysis and (iii) panel analysis.

4.5.1 Machine learning

The first empirical analysis is based on the application of supervised machine learning algorithms of classification to predict the outcome of ECF campaigns and was conducted together with the Department of Information Engineering of the Marche Polytechnic University via the Python computer programming language[2]. The empirical analysis focused on a subsample of the cross-sectional dataset taking as inputs the extracted features (variables) of the ECF campaigns. The aim of the models is to learn the outcome of a campaign (success/failure) from a labelled sample (training set) and exploit such learned knowledge to predict the outcome on a new unlabeled sample (test set). Six machine learning classification algorithms were applied:

(i) *K-Nearest Neighbors (K-NN):* is a non-parametric classification method (Fix and Hodges, 1989; Cover and Hart, 1967) that compares instances in the training dataset based on a similarity measure to find best matches. In predictive classification it takes as input the k-closest training observations to assign an unlabeled observation to a class (success/failure).

(ii) *Gaussian Naïve Bayes:* applies Bayes' Theorem for classification by fitting a probability function constructed via a naive simplification of Bayes and following a Gaussian normal distribution.

(iii) *Classification and Regression Tree (CART):* is a non-parametric algorithm that belongs to the Decision Tree models of decision (Breiman et al., n.d.). These models involve stratifying or segmenting the predictor space into a number of regions following a set of splitting rules that can be summarized with a tree structure. It is based on data attribute, where predictions are made by sorting the observations down the tree from the root to some leaf/terminal node, with the leaf/terminal node providing the classification of the example.

[2] I would like to thank prof. Caterina Lucarelli, prof. Emanuele Frontoni, Prof. Marina Paolanti, Ph.D. Rocco Pietrini and Dott. Marco Mameli for their expertise and support in this collaboration.

(iv) *Random Forest:* is an ensemble algorithm of classification belonging to the Decision Tree models that is based on the aggregation of multiple decision trees (CARTs) relatively uncorrelated.

(v) *Adaptive Boosting (AdaBoost):* is an algorithm that produces highly accurate prediction rules by combining into a weighted sum the output of many relatively weak (weak learners) algorithms (Freund and Schapire, 1997).

(vi) *Multilayer Perceptron (MLP):* is based on the combination of many binary classification algorithms, namely Perceptrons, that constitutes an artificial (non-deep) neural network. It models relaationships between a set of predictors and a response variable. The output is generated by the sum of weighted inputs given by several Perceptrons, stacked in layers, and adding a bias factor. Each node (neuron) uses a nonlinear activation function, namely the backpropagation algorithm.

4.5.2 Cross-sectional

In the second empirical setting (Panel A) data is analyzed in a cross-sectional perspective that takes into account the static nature of aggregated data retrieved at the conclusion of the campaigns. The method of analysis is based on multivariate econometric regressions, and in particular on linear regressions (OLS) and logistic regressions (Logit). The model specifications are presented respectively in equation 4.1 and 4.2. The analysis is conducted using the software STATA/SE 15.1.

$$\begin{gathered} Capitalraised = \alpha + \beta_0 EquityRetention_i + \beta_1 Premoney_i + \\ \beta_2 InvestorsNumber_i + \beta_3 SocialCount_i + \beta_4 SocialPresence_i + \\ \beta_5 GeographicalProximity_i + \delta_1 Controls_i + \varepsilon \end{gathered} \tag{4.1}$$

$$\begin{gathered} Success = Pr[Y_i = 1|X_i] = \frac{e^{(\gamma_0 + \gamma_1 X_i + \delta_1 Controls_i)}}{1 + e^{(\gamma_0 + \gamma_1 X_i + \delta_1 Controls_i)}} \\ Logit = Ln\left[\frac{Pr}{1 - Pr}\right] = \gamma_0 + \gamma_1 X_i + \delta_1 Controls_i \end{gathered} \tag{4.2}$$

4.5.3 Panel

In the third empirical setting (Panel B) data is analyzed in a longitudinal perspective that takes into account both the cross-sectional and the time-varying nature of aggregated data retrieved at a weekly frequency. The method of analysis is based on multivariate panel-data econometric models, and in particular on pooled linear regressions

(POLS), panel-data fixed-effects regressions (FE), random-effects regressions (RE). The model specifications are presented respectively in equation 4.3, 4.4 and 4.5.The analysis is conducted using the software STATA/SE 15.1.

$$\begin{aligned} CapitalRaised_i = \alpha + \beta_0 EquityRetention_i + \beta_1 Premoney_i + \beta_2 PercentageRaised_i + \\ \beta_3 InvestorsNumber_i + \beta_4 SocialCount_i + \beta_5 SocialPresence_i + \\ \beta_6 GeographicalProximity_i + \delta_1 Controls_i + \varepsilon_i \end{aligned} \tag{4.3}$$

$$\begin{aligned} CapitalRaised_{i,t} = \alpha + \beta_0 EquityRetention_{i,t} + \beta_1 Premoney_{i,t} + \beta_2 PercentageRaised_{i,t} + \\ \beta_3 InvestorsNumber_{i,t} + \beta_4 SocialCount_{i,t} + \beta_5 SocialPresence_{i,t} + \\ \beta_6 GeographicalProximity_{i,t} + \delta_1 Controls_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \end{aligned} \tag{4.4}$$

$$\begin{aligned} CapitalRaised_{i,t} = \alpha + \beta_0 EquityRetention_{i,t} + \beta_1 Premoney_{i,t} + \beta_2 PercentageRaised_{i,t} + \\ \beta_3 InvestorsNumber_{i,t} + \beta_4 SocialCount_{i,t} + \beta_5 SocialPresence_{i,t} + \\ \beta_6 GeographicalProximity_{i,t} + \delta_1 Controls_{i,t} + \tau_t + \upsilon_{i,t} \end{aligned} \tag{4.5}$$

4.6 Results

4.6.1 Descriptive statistics

Table 4.11 reports the main descriptive statistics of our cross-sectional sample (Panel A), in terms of univariate statistics: observations, mean, median, standard deviation, minimum and maximum values. The sample comprises 2,177 observations of campaigns concluded by July 2020 from ten platforms. The average success rate of the campaigns is 75% with a standard deviation of 0.43. The average level of equity retained by entrepreneurs is 90.66%, with a standard deviation of 7.30. In other words, on average 9.34% of equity shares are offered to investors. Less than half of the campaigns sampled (47%) have online presence on social media. If we consider the social media count, half of the sample provide access to less than one social media (0.58 out of 4 considered). The two other dummy variables, presence of professional investors and geographical proximity, respectively show mean values of 82% and 85%. Another variable worth of consideration is the percentage of funding raised that exhibits a mean of 1.55 (155%), showing that projects that reaches the target typically get overfunded. It becomes evident that the observation distribution is heterogeneous among variables. As previously stated, the reason

	Obs.	Mean	Median	Std. Dev	Min	Max
Capital raised in EUR	1879	662537.55	224001.12	1399068.86	0.00	17299922
Capital raised (log)	1879	11.84	12.32	2.88	0.00	17
Campaign success	1690	0.75	1.00	0.43	0.00	1
Equity retention	1258	90.66	92.30	7.30	2.00	100
Pre-money valuation	547	5910411.37	2500000.00	15777742.14	1000.00	251000000
Pre-money valuation (log)	547	14.77	14.73	1.22	6.91	19
Presence of professional investors	145	0.82	1.00	0.38	0.00	1
Percentage of capital raised	1617	1.55	1.16	5.03	0.00	195
Number of investors	699	413.28	245.00	644.02	0.00	10363
No. social media	1914	0.58	0.00	0.73	0.00	4
Presence on social media	1914	0.47	0.00	0.50	0.00	1
Geographical proximity	1432	0.85	1.00	0.36	0.00	1
Covid period	2177	0.17	0.00	0.38	0.00	1
Minimum investment target	1592	546197.72	224003.36	1235533.55	500.00	21000000
Log min funding goal	1592	12.35	12.32	1.28	6.22	17
Maximum investment target	307	511938.34	400000.00	746438.03	30000.00	8000000
Log max funding goal	307	12.78	12.90	0.78	10.31	16
Entrepreneur gender	908	0.16	0.00	0.37	0.00	1
Entrepreneur age	309	45.29	45.00	11.09	23.00	76
Entrepreneur seniority	312	3.68	3.00	2.77	0.00	17
Firm age	313	4.65	4.00	3.23	0.00	22
Price per share	950	1641.71	100.00	5491.80	0.01	50000
Equity	97	100194.10	11111.11	530247.43	100.00	5159866
Largest investment	62	375955.10	77876.00	1422036.28	5012.00	10500000
Interested investors	321	825.48	511.00	1375.48	1.00	16836
Presence on Facebook	1447	0.24	0.00	0.43	0.00	1
Presence on Twitter	1548	0.21	0.00	0.41	0.00	1
Presence on LinkedIn	1307	0.23	0.00	0.42	0.00	1
Presence on Instagram	1473	0.09	0.00	0.29	0.00	1
Country	2177	5.13	6.00	1.69	1.00	7
Platform	2177	4.71	5.00	2.44	1.00	10
Observations	2177					

Table 4.11: Summary statistics of Panel A

mainly lies in the heterogeneous sets of information provided by different platforms for each campaign. Table 4.12 provides an overview of the observation count for each variable among the different platforms considered in our study. As for the panel dataset (Panel B), table 4.13 reports the main descriptive statistics. The sample comprises 737 longitudinal observations of campaigns concluded by October 2020 from three platforms. Similarly to Panel A, the observation distribution appears heterogeneous across the variables. To this end, it is worth considering that due to the aforementioned (see subsection 4.4.4 "Variables description") heterogeneous information disclosure from the platforms, sample size may vary across the models, as variables might be missing for certain platforms, resulting sometimes in a decrease of the observation count.

Table 4.14 provides an overview of the observation distribution for each variable among

	(1) Crowdcube **Obs.**	(2) Fundedbyme **Obs.**	(3) Invesdor **Obs.**	(4) Mamacrowd **Obs.**	(5) Seedrs **Obs.**	(6) Sowefund **Obs.**	(7) Crowdfunder **Obs.**	(8) Opstart **Obs.**	(9) 200Crowd **Obs.**	(10) Companisto **Obs.**
Capital raised in EUR	312	197	140	97	748	13	134	80	48	110
Capital raised (log)	312	197	140	97	748	13	134	80	48	110
Campaign success	314	36	146	97	741	94	134	80	48	0
Equity retention	307	195	1	97	610	0	0	0	48	0
Pre-money valuation	303	0	7	97	12	0	0	80	48	0
Pre-money valuation (log)	303	0	7	97	12	0	0	80	48	0
Presence of professional investors	0	0	0	97	0	0	0	0	48	0
Percentage of capital raised	314	0	146	97	741	57	134	80	48	0
Number of investors	314	3	4	97	132	0	0	0	48	101
No. social media	314	213	153	97	769	0	288	80	0	0
Presence on social media	314	213	153	97	769	0	288	80	0	0
Geographical proximity	313	213	153	97	273	96	287	0	0	0
Covid period	314	213	153	97	769	104	288	80	48	111
Minimum investment target	312	3	146	97	675	97	134	80	48	0
Log min funding goal	312	3	146	97	675	97	134	80	48	0
Maximum investment target	0	1	0	97	0	81	0	80	48	0
Log max funding goal	0	1	0	97	0	81	0	80	48	0
Entrepreneur gender	312	0	121	97	1	33	264	80	0	0
Entrepreneur age	309	0	0	0	0	0	0	0	0	0
Entrepreneur seniority	312	0	0	0	0	0	0	0	0	0
Firm age	313	0	0	0	0	0	0	0	0	0
Price per share	10	1	2	97	423	104	127	79	0	107
Equity	0	0	0	97	0	0	0	0	0	0
Largest investment	52	0	0	0	10	0	0	0	0	0
Interested investors	224	39	0	0	10	0	0	0	48	0
Presence on Facebook	0	213	0	97	769	0	288	80	0	0
Presence on Twitter	314	0	0	97	769	0	288	80	0	0
Presence on LinkedIn	0	0	153	97	769	0	288	0	0	0
Presence on Instagram	314	213	0	97	769	0	0	80	0	0
Observations	314	213	153	97	769	104	288	80	48	111

Table 4.12: Observation distribution per platform of Panel A

	Obs.	**Mean**	**Median**	**Std. Dev**	**Min**	**Max**
timespan	737	3.38	3.00	2.04	1.00	12
Capital raised in EUR	737	653009.75	270000.00	1210141.44	21667.00	11340160
Capital raised (log)	737	12.65	12.51	1.11	9.98	16
Campaign success	737	0.68	1.00	0.47	0.00	1
Equity retention	525	91.58	92.86	5.74	66.71	99
Premoney valuation	509	8182744.19	3500000.00	17174657.15	550000.00	150821907
Premoney (log)	509	15.18	15.07	1.07	13.22	19
Percentage raised	737	1.40	1.12	0.94	0.33	9
Number of investors	734	409.75	239.50	664.31	20.00	10363
No. social media	737	1.28	1.00	0.78	0.00	3
Presence social media	737	0.92	1.00	0.28	0.00	1
Geographical proximity	737	0.88	1.00	0.32	0.00	1
Min investment target	737	432229.75	250000.00	613644.50	40000.00	5000000
Minimum investment target (log)	737	12.46	12.43	0.96	10.60	15
Entrepreneur gender	303	0.12	0.00	0.32	0.00	1
Entrepreneur age	289	45.02	43.00	10.32	24.00	72
Entrepreneur seniority	281	3.02	2.00	2.79	0.00	14
Firm age	281	3.78	3.00	3.04	0.00	13
Price per share	90	2.58	2.08	2.30	0.13	9
Largest investment	285	280114.93	50368.00	1131040.91	5012.00	10500000
Interested investors	289	1133.44	625.00	2047.45	74.00	17351
Presence on Facebook	723	0.18	0.00	0.38	0.00	1
Presence on Twitter	723	0.35	0.00	0.48	0.00	1
Presence on LinkedIn	448	0.77	1.00	0.42	0.00	1
Presence on Instagram	289	0.74	1.00	0.44	0.00	1
Platform	737	2.20	3.00	0.97	1.00	3
Country	737	1.98	2.00	0.14	1.00	2
Observations	737					

Table 4.13: Summary statistics of Panel B

the different platforms considered in Panel B.

	(1) Crowdcube **Obs.**	(2) Invesdor **Obs.**	(3) Seedrs **Obs.**
timespan	289	14	434
Capital raised in EUR	289	14	434
Capital raised (log)	289	14	434
Campaign success	289	14	434
Equity retention	248	14	263
Premoney valuation	248	14	247
Premoney (log)	248	14	247
Percentage raised	289	14	434
Number of investors	289	11	434
No. social media	289	14	434
Presence social media	289	14	434
Geographical proximity	289	14	434
Min investment target	289	14	434
Minimum investment target (log)	289	14	434
Entrepreneur gender	289	14	0
Entrepreneur age	289	0	0
Entrepreneur seniority	281	0	0
Firm age	281	0	0
Price per share	90	0	0
Largest investment	285	0	0
Interested investors	289	0	0
Presence on Facebook	289	0	434
Presence on Twitter	289	0	434
Presence on LinkedIn	0	14	434
Presence on Instagram	289	0	0
Platform	289	14	434
Country	289	14	434
Observations	289	14	434

Table 4.14: Observation distribution per platform of Panel B

4.6.2 Classification

The classification analysis is based on a sub-sample of data extracted from the ten platforms, taken as a training test to build supervised machine learning algorithms. Starting from a correlation matrix (figure 4.3), different algorithms tried to predict the output of ECF campaigns in the test set based on the observation of the training set. Seven attributes are chosen via feature selection (Correlation-based Feature Selection, CFS; Hall et al., 1999): label (success/failure dummy), funding goal, capital raised, pre-money valuation, largest investment, percentage of funding and shares offered (100%-equity retention). Table 4.15 shows the model evaluations. The performance indicators suggest that the most accurate classification methods appear to be: KNN, AdaBoost, Decision Tree, Random Forest and Multilayer Perceptron. The Gaussian Naïve Bayes, instead, results the most distorted. However, the accuracy of the AdaBoost method raises concerns. Indeed, although it appears to be very good in predicting positive labels, its overall performance in predicting all the labels is distorted. This appears evident in figure 4.4,

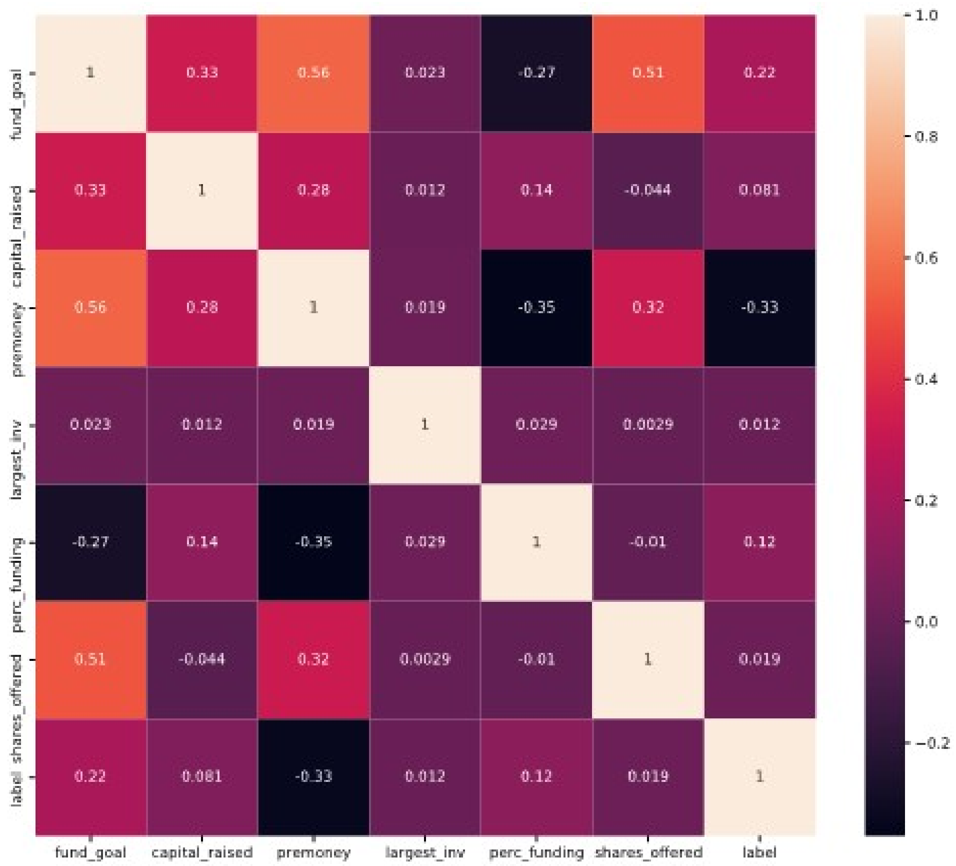


Figure 4.3: Correlation matrix

Measure	KNN	Gaussian NB	AdaBoost	Decision Tree	Random Forest	MLP
Precision	0.957597	1	1	0.971223	0.978571	0.956989
Recall	0.985455	0.00727273	0.996364	0.981818	0.996364	0.970909
F1-Score	0.971326	0.0144404	0.998179	0.976492	0.987387	0.963899
Accuracy	0.949045	0.130573	0.996815	0.958599	0.977707	0.936306

Table 4.15: Performance indicators of the algorithms

where the confusion matrices allow the visualization of the overall performance of the algorithms. Results of classification methods are depicted in table 4.16. Among the seven attributes that were initially taken into consideration, the models ultimately selected features depicted in green; features depicted in red, instead, appear not to be significant in labelling success for the respective classification method.

It is important to note here that the classification analysis is undertaken as an exploratory analysis to identify and assign features to a sub-sample of data with the aim to allow for subsequent more accurate analysis via econometric modeling. Indeed, the exploratory analysis of the ten platforms serves not only to provide an overview of the phenomenon, but also to identify which categories an observation belongs to and gather

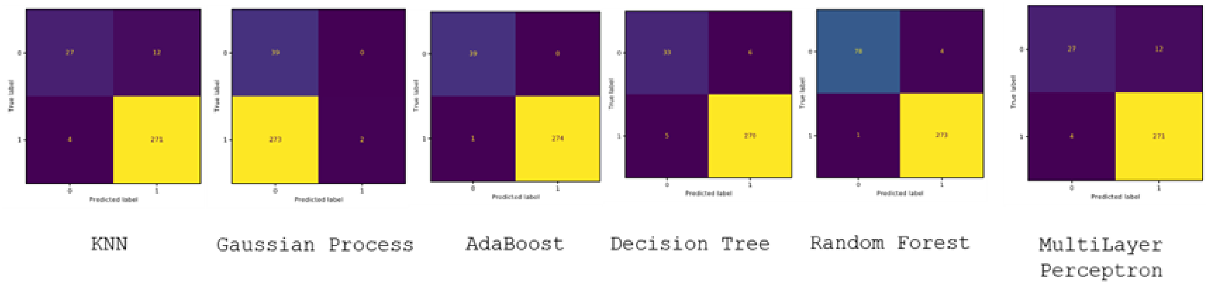


Figure 4.4: Confusion matrices

	Models				
Features	*KNN*	*Decision Tree*	*Random Forest*	*AdaBoost*	*Multilayer Perceptron*
Equity retention					
Premoney					
Percentage of funding					
Number of investors					
Capital raised					
Funding goal					
Largest investment					

Table 4.16: Results of classification methods

a preliminary insight of the set of features identified with labelled successful campaigns upon which building the econometric analysis.

4.6.3 Determinants of ECF success

Table 4.17 shows the results of the linear multivariate regressions with OLS algorithm at the cross-sectional level (Panel A). Five different models are built to test the effects of different sets of explanatory and control variables on the overall bids made by investors (amount of capital raised). Logarithmic transformation of both dependent variable and independent monetary variables are adopted to reduce skewness, improve the fit of the models and highlight relative changes in parameters (Lukkarinen et al., 2016).

Model 1 is an aggregate multi-platform model on 399 observations that include a baseline specification. Model 2 is a single-platform model that includes 300 observations from Crowdcube. It consists of a baseline specification. Model 3 is a single-platform model that includes 296 observations from Crowdcube. A set of control variables is added to the baseline specification. Model 4 is a single-platform model that includes 97 observations from Mamacrowd. It consists of a baseline specification. Model 5 is a single-platform model that includes 97 observations from Mamacrowd. A set of control variables is added to the baseline specification. The aggregate Model 1, with a R-squared of 67%, present significant coefficients for *equity retention, pre-money valuation, percentage of capital raised, number of investors, number of social media, presence on social media, geographical proximity* and *covid period.* Surprisingly, a higher equity share retained by the entrepreneurs is associated with lower amounts of capital raised for Models 1,2 and 4. The evaluation of the venture made by experts (pre-money) is associated with higher amounts of capital raised. This effect appears significant (p-value¡0.01) among the five models (with coefficients ranging between 0.453 and 0.751), with the exception of model 3, where control variables are applied to Crowdcube.

Similarly, the financial engagement and the wisdom-of-the-crowd have a positive effect on the amount raised, showing significant signaling properties.

As far as social media network is concerned, the number of social media accounts appears to have a negative relationship with capital raised for the aggregate model (1). However, disentangling the effect among the platforms, we find that a non-significant relationship is present in crowdcube, whether the negative effect is mainly driven by the platform Mamacrowd (models 4 and 5). The online presence, instead, show a positive impact for the aggregate model, whether it turns negative for Mamacrowd, in line with findings on the number of accounts. Geographical proximity exhibits a surprising negative impact on the amount of capital raised in the aggregate model, but no significative effect is found among the platform-centered models. Overall, the amount of capital raised is characterized by higher shares of equity offered to investors, higher pre-money valuations, higher percentage of capital raised, higher numbers of investors, online presence on social media but with lower number of accounts, geographical heterogeneity, higher transactions within the covid-19 pandemic and higher funding targets (model 3) and higher funding caps (model 5). Table 4.18 shows the results of the logistic regressions at the cross-sectional level (Panel A). To the same extent of the linear multivariate regressions, five different logistic regression models are built to test the effects of different sets of explanatory and control variables on the campaign success. However, Model 5 is dropped due to multicollinearity issues of the set of control variables. Overall, determinants of the amount of capital raised tend to slightly differ from the determinants of success. Indeed, success of an ECF campaigns appears to be characterized by higher shares of equity retained by entrepreneurs, lower pre-money valuations, higher number of investors, no

Capital raised (log)	(1) **Aggregate** *Coef./(Std. err.)*	(2) **Crowdcube-A** *Coef./(Std. err.)*	(3) **Crowdcube-B** *Coef./(Std. err.)*	(4) **Mamacrowd-A** *Coef./(Std. err.)*	(5) **Mamacrowd-B** *Coef./(Std. err.)*
Equity retention	-0.049***	-0.065***	-0.004	-0.055**	-0.041
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
Pre-money valuation (log)	0.741***	0.751***	0.064	0.550**	0.453*
	(0.10)	(0.04)	(0.04)	(0.27)	(0.27)
Percentage of capital raised	0.320***	0.181***	0.432***	0.418**	0.234
	(0.07)	(0.03)	(0.03)	(0.20)	(0.22)
Number of investors	0.000**	0.000**	-0.000	0.005***	0.003*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. social media	-2.820***	-0.292	0.016	-1.425***	-1.062***
	(0.16)	(0.61)	(0.39)	(0.37)	(0.40)
Presence on social media	2.007***	0.313	0.047	-1.608	-2.393*
	(0.31)	(0.61)	(0.39)	(1.32)	(1.31)
Geographical proximity	-0.607**	-0.114	-0.078	0.000	0.000
	(0.28)	(0.10)	(0.06)	(.)	(.)
Covid period	0.505**	-0.033	0.010	1.468	1.512*
	(0.24)	(0.09)	(0.06)	(0.91)	(0.89)
Log min funding goal			0.939***		0.227
			(0.05)		(0.59)
Entrepreneur seniority			-0.002		
			(0.01)		
Firm age			0.014		
			(0.01)		
Entrepreneur gender			-0.026		
			(0.06)		
Entrepreneur age			0.002		
			(0.00)		
Presence of professional investors					1.884**
					(0.92)
(Log) share price					-0.431
					(0.44)
Log max funding goal					1.192**
					(0.58)
Equity					-0.000*
					(0.00)
constant	5.535***	6.825***	-0.380	6.857**	-9.447
	(1.39)	(0.77)	(0.67)	(3.32)	(8.23)
R-squared	0.67	0.72	0.89	0.48	0.57
AIC	1613.62	560.90	289.97	486.79	478.13
BIC	1649.52	594.24	341.63	507.39	511.60
N. of cases	399	300	296	97	97

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4.17: Results of linear multivariate regression models

	(7)	(8)	(9)	(10)	(11)
	Aggregate	**Crowdcube-A**	**Crowdcube-B**	**Mamacrowd-A**	**Mamacrowd-B**
Campaign success	*Coef./(Std. err.)*	*Coef./(Std. err.)*	*Coef./(Std. err.)*	*Coef./(Std. err.)*	*Coef./(Std. err.)*
Equity retention	0.093***	0.171***	0.057	0.989	12.445
	(0.03)	(0.05)	(0.07)	(0.61)	(.)
Pre-money valuation (log)	-0.723***	-1.792***	-1.161***	-11.922	-75.949
	(0.22)	(0.35)	(0.45)	(8.11)	(.)
Number of investors	0.012***	0.007***	0.003	0.371	4.461
	(0.00)	(0.00)	(0.00)	(0.24)	(.)
No. social media	0.960**	15.879	19.359	-4.587	-7.170
	(0.46)	(1664.32)	(5831.17)	(4.33)	(.)
Presence on social media	-1.159*	-16.067	-19.113	2.709	-27.622
	(0.62)	(1664.32)	(5831.17)	(62.94)	(.)
Geographical proximity	-0.349	-0.427	0.199	0.000	0.000
	(0.49)	(0.57)	(0.78)	(.)	(.)
Covid period	0.132	0.231	0.219	0.113	-26.553
	(0.40)	(0.46)	(0.62)	(3.27)	(.)
Capital raised (log)	0.500***	2.508***	7.637***	-0.151	2.690
	(0.14)	(0.42)	(1.27)	(0.48)	(.)
FIN	0.000				
	(.)				
ITA	4.691***			0.000	0.000
	(0.99)			(.)	(.)
UK	0.000	0.000	0.000		
	(.)	(.)	(.)		
Log min funding goal			-6.085***		18.771
			(1.12)		(.)
Entrepreneur seniority			-0.066		
			(0.22)		
Firm age			0.172		
			(0.20)		
Entrepreneur gender			-1.070*		
			(0.57)		
Entrepreneur age			0.003		
			(0.02)		
(Log) share price					30.419
					(.)
Log max funding goal					-25.995
					(.)
Equity					-0.000
					(.)
constant	-5.143*	-19.571***	-7.135	82.921	-197.413
	(2.85)	(5.41)	(8.31)	(98.66)	(.)
Pseudo-R2	0.46	0.55	0.79	0.86	1.00
AIC	290.13	196.69	133.72	25.87	0.00
BIC	330.00	230.02	185.38	46.47	0.00
N. of cases	398	300	296	97	97

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4.18: Results of logistic regression models

online presence, but if any the higher number of accounts the better, lower funding goals and apparently male entrepreneurial teams (Crowdcube).

4.6.4 Results from the panel-data analysis

In Panel B, time-varying effects (longitudinal dataset) are introduced. Table 4.20 shows the results from the panel-data analysis at the aggregated level from three platforms (Crowdcube, Invesdor and Seedrs). The panel dataset appears unbalanced with 153 individuals (campaigns) over 12 time periods. The pattern and cumulate distribution of data per timespans is shown in table 4.19.

Three econometric models are built: pooled OLS (POLS), Fixed individual effects (FE) and Random individual effects (RE). In Panel B only the variable amount of capital raised is used as dependent variable. The reason is that a dummy variable for the outcome of a campaign cannot entirely capture the funding dynamics, especially in case of overfunding. A continuous variable, instead, is able to seize the effects of different sets of explanatory and control variables on the overall bids made by investors (amount of capital raised) during time and also during the overfunding phase (if any). POLS

Freq.	**Percent**	**Cum.**	**Pattern**			
28	18.30	18.30	111111......			
26	16.99	35.29	11..........			
26	16.99	52.29	11111.......			
21	13.73	66.01	1111........			
19	12.42	78.43	111.........			
15	9.80	88.24	1111111.....			
8	5.23	93.46	11111111....			
5	3.27	96.73	111111111...			
2	1.31	98.04	1...........			
3	1.96	100.00	(other patterns)			
153	100.00					
Distribution of t_i						
Min	*5%*	*25%*	*50%*	*75%*	*95%*	*max*
1	2	3	5	6	8	12

Table 4.19: Pattern description of data

implies the hypothesis of homogeneous dynamics of different campaigns both in slope and intercept. However, panel-data poolability leads inevitably to heterogeneity bias as it ignores individual heterogeneities. Due to this limitation, the POLS model serves only as a starter for panel-data analysis, in order to seize (if any) the differences in individual fixed effects. Table 4.20 displays the results from the POLS regressions at the aggregate (model 1) and individual levels for each platform (models from 2 to 4). Models 2 and 3 are applied to the platform Crowdcube at both the baseline specification (Model 2) and with an additional set of control variables (Model 3).

Fixed-effects models applies data demeaning (within-groups estimators) to capture individual unmeasurable characteristics that may influence the relationship between dependent and explanatory variables.

Table 4.21 displays the results from the FE regressions at the aggregate (model 1) and individual levels for each platform (models from 2 to 4), with clustered robust standard errors within each campaign. Models 2 and 3 are applied to the platform Crowdcube at both the baseline specification (Model 2) and with an additional set of control variables (Model 3). The models test the effects of different sets of explanatory and control variables on the overall bids made by investors (amount of capital raised), with time-varying effects and individual heterogeneities. Models are applied with time-effects controls (omitted from the table). Random-effects models consider individual effects as random and ignores the specific nature of the individual heterogeneity. For this reason, RE models are also known as error-component models, as the individual effects become part of the model error. RE estimations adopts Feasible Generalized Least Squares (FGLS) algorithms to eliminate serial correlation in the error term.

Table 4.22 shows the results from the RE regressions at the aggregate (model 1) and individual levels for each platform (models from 2 to 4), where models on Crowdcube are applied at both the baseline specification (Model 2) and with an additional set of control variables (Model 3). The models test the effects of different sets of explanatory and control variables on the overall bids made by investors (amount of capital raised), with time-varying effects, and non-observable heterogeneity. Models are applied with time-effects controls (omitted from the table). To choose between FE and RE models, a Hausman test is performed (Hausman, 1978). The statistic test compares the two estimators evaluating their consistency. The result of the test suggests using the RE models as systematic difference in coefficient is not detected, thus revealing that the RE model is unbiased and efficient.

Table 4.23 reports the results from the aggregate models of POLS (Model 1), FEc (Model 2) and RE (Model 3). Following the Hausman test, RE regressions are considered for the following discussion of results. Results from the RE models reported in Table

Y∼Capital raised in thousands	(1) **Aggregate** Coef./(Std. err.)	(2) **Crowdcube** Coef./(Std. err.)	(3) **Crowdcube-B** Coef./(Std. err.)	(4) **Seedrs** Coef./(Std. err.)
Equity retention	5.95*	15.94***	15.63***	1.51
	(3.10)	(5.53)	(4.36)	(4.01)
Premoney valuation	0.00***	-0.00	-0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Percentage raised	332.58***	221.18***	105.10***	554.53***
	(20.76)	(25.71)	(21.51)	(37.70)
Number of investors	0.12***	0.32***	0.72***	-0.49***
	(0.04)	(0.05)	(0.07)	(0.12)
No. social media	-60.29**	-194.36***	-126.74**	-61.64**
	(24.37)	(71.96)	(53.28)	(28.95)
Presence social media	-19.19	-307.26**	-344.67***	201.23***
	(60.65)	(132.66)	(97.44)	(76.64)
Geographical proximity	5.54	-103.20*	43.46	3.77
	(44.27)	(59.44)	(44.51)	(69.59)
FIN	0.00			
	(.)			
UK	203.13*			0.00
	(105.65)			(.)
Min investment target	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Interested investors			-0.02	
			(0.05)	
Largest investment			0.00***	
			(0.00)	
Remaining days to closing campaign			3.97***	
			(1.41)	
Firm age			-1.04	
			(7.71)	
Entrepreneur gender			41.87	
			(42.86)	
Entrepreneur age			-3.18**	
			(1.54)	
Entrepreneur seniority			7.69	
			(6.47)	
constant	-1241.52***	-1401.97***	-1326.73***	-934.48**
	(311.44)	(517.56)	(392.35)	(380.25)
N	506	248	248	247
df	9	8	15	8
R2	0.85	0.89	0.95	0.87
RMSE	331.80	273.70	197.82	328.02

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4.20: Results of POLS at aggregated and individual levels

	(1) **Aggregate**	(2) **Crowdcube**	(3) **Crowdcube-B**	(4) **Seedrs**
Capital raised in thousands	*Coef./(Std. err.)*	*Coef./(Std. err.)*	*Coef./(Std. err.)*	*Coef./(Std. err.)*
Equity retention	81.44***	46.89***	48.11***	0.00
	(29.48)	(14.07)	(14.72)	(.)
Premoney valuation	-0.00**	-0.00***	-0.00*	0.00
	(0.00)	(0.00)	(0.00)	(.)
Percentage raised	385.90***	219.18***	230.06***	447.05*
	(140.86)	(51.85)	(52.27)	(228.48)
Number of investors	0.44***	0.53***	0.29	0.63
	(0.09)	(0.03)	(0.18)	(0.59)
No. social media	22.82	0.00	0.00	-5.10
	(17.48)	(.)	(.)	(87.43)
Min investment target	0.00**	0.00	0.00	-7.05
	(0.00)	(0.00)	(0.00)	(90.16)
Interested investors			0.22	
			(0.14)	
Largest investment			0.00**	
			(0.00)	
Remaining days to closing campaign			2.86*	
			(1.71)	
constant	-7602.37***	-4600.75***	-5473.46***	2462593.98
	(2703.64)	(1446.99)	(1521.12)	(31507285.92)
NT	506	248	248	247
df	11	10	13	9
Time effects	Yes	Yes	Yes	Yes
Between-var	1877.28	801.36	1972.69	2922702.85
Within-var	199.04	100.99	98.81	259.87
R2-within	0.64	0.87	0.88	0.51
RMSE	176.25	88.32	86.25	231.69

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4.21: Results of FE (with clustered s.e.) at aggregated and individual levels

4.22 and Table 4.23 (Model 3) present, with a R-squared of 84% for the aggregate model, significant coefficients for equity retention, pre-money valuation, percentage of capital raised, number of investors, funding goal. Accounting for time-varying effects, higher equity shares retained by entrepreneurs attracts higher amounts of capital, and this is particularly true ($p - value < 0.01$) on the platform Crowdcube. Surprisingly, in this sample the evaluation of the venture made by experts (pre-money) is associated with lower amounts of capital raised, even though the impact appears low in coefficient and turns out to be non-significant for the platform Seedrs.

Applying time-varying effects, the financial engagement and the wisdom-of-the-crowd have a positive and strong effect on the amount raised, showing significant herding behaviour from investors, even though the number of investors becomes non-significant for investors in the platform Seedrs. The online presence on social media presents an ambiguous effect. Although it appears to be a determinant factor for the platform Seedrs

Capital raised in thousands	(1) **Aggregate** *Coef./(Std. err.)*	(2) **Crowdcube** *Coef./(Std. err.)*	(3) **Crowdcube-B** *Coef./(Std. err.)*	(4) **Seedrs** *Coef./(Std. err.)*
Equity retention	21.00***	35.84***	27.00***	3.07
	(6.20)	(7.99)	(6.57)	(6.87)
Premoney valuation	-0.00**	-0.00***	-0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Percentage raised	356.51***	216.07***	170.55***	542.03***
	(23.94)	(25.61)	(24.15)	(44.90)
Number of investors	0.37***	0.52***	0.53***	-0.16
	(0.04)	(0.03)	(0.08)	(0.15)
Presence social media	-20.39	-101.76	-566.32***	230.31*
	(119.44)	(314.36)	(202.24)	(119.97)
No. social media	-76.58	-330.01*	-105.91	-80.19*
	(48.10)	(176.29)	(112.80)	(45.65)
Geographical proximity	-52.92	-207.13	69.39	-46.45
	(89.87)	(133.02)	(88.71)	(113.97)
Min investment target	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Interested investors			0.04	
			(0.07)	
Largest investment			0.00***	
			(0.00)	
Remaining days to closing campaign			1.24	
			(1.84)	
Firm age			3.70	
			(16.05)	
Entrepreneur gender			111.65	
			(86.38)	
Entrepreneur age			-3.25	
			(2.97)	
Entrepreneur seniority			5.15	
			(14.01)	
constant	-2446.18***	-3246.55***	-2248.99***	-1077.68*
	(597.93)	(809.45)	(624.48)	(644.19)
NT	506	248	248	247
df	16	16	23	16
Time effects	Yes	Yes	Yes	Yes
Between-var	292.17	309.16	178.32	197.63
Within-var	199.04	100.99	98.81	259.87
R2-overall	0.84	0.88	0.94	0.87
R2-within	0.62	0.87	0.87	0.48
R2-between	0.89	0.91	0.97	0.93
RMSE	205.02	103.09	104.76	267.94

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4.22: Results of RE at aggregated and individual levels

	(1)	(2)	(3)
	POLS	**FEc**	**RE**
Capital raised in thousands	*Coef./(Std. err.)*	*Coef./(Std. err.)*	*Coef./(Std. err.)*
Equity retention	5.95*	81.44***	21.00***
	(3.10)	(29.48)	(6.20)
Premoney valuation	0.00***	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)
Percentage raised	332.58***	385.90***	356.51***
	(20.76)	(140.86)	(23.94)
Number of investors	0.12***	0.44***	0.37***
	(0.04)	(0.09)	(0.04)
No. social media	-60.29**	22.82	-76.58
	(24.37)	(17.48)	(48.10)
Presence social media	-19.19	0.00	-20.39
	(60.65)	(.)	(119.44)
Geographical proximity	5.54	0.00	-52.92
	(44.27)	(.)	(89.87)
Min investment target	0.00***	0.00**	0.00***
	(0.00)	(0.00)	(0.00)
constant	-1241.52***	-7602.37***	-2446.18***
	(311.44)	(2703.64)	(597.93)
NT	506	506	506
df	9	11	16
Time effects	No	Yes	Yes
Between-var	/	1877.28	292.17
Within-var	/	199.04	199.04
R2	0.85	0.08	0.84
R2-within	/	0.64	0.62
R2-between	/	0.20	0.89
RMSE	331.80	176.25	205.02

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4.23: Results of aggregated panel-data models

but with low significance ($p - value < 0.1$), it turns out to have a significant negative impact on the amount raised for investors in Crowdcube, when controlling for firm specifics, investor specifics and entrepreneur specifics. At the aggregate level, instead, the effect is non-significant. The number of social media accounts does not show a significant effect at the aggregate level. However, when decomposing the models at the individual platform levels, it appears to have a negative effect on the amount raised for Crowdcube and Seedrs, even though with scarce significance ($p - value < 0.1$). The geographical proximity exhibits non-significant effects. Overall, the amount of capital raised is bolstered by higher shares of equity retained by entrepreneurs, apparently lower pre-money valuations, higher percentage of capital raised, higher numbers of investors, and higher funding targets (with the exception of the platform Invesdor). Apparently, investors in the Finnish platform Invesdor are concentrated in the early days of a campaign and prefer lower funding goals to be reached.

4.6.5 Additional results

Few platforms only provided explicit information about the presence of professional investors. For this reason, it was hard to test hypothesis 3 with previous aggregate models due to the paucity of observations. Therefore, a subsample of the cross-sectional dataset was used as robustness test to assess the impact of this variable on investments that had publicly access to this information. In particular, data from both Mamacrowd and 200Crowd was gathered, as they were the only two platforms to declare the presence of institutional/professional investors. Results from table 4.24 show the restricted regression models performed. Hypothesis 3 cannot be rejected, as the variable seem to have a strong and significant impact on both the amount of capital raised and the outcome of an ECF campaign.

	(1) **OLS** *Coef./(Std. err.)*	(2) **Logit** *Coef./(Std. err.)*
Equity retention	-0.081***	-0.277
	(0.03)	(0.18)
Pre-money valuation (log)	0.795**	3.542
	(0.32)	(2.23)
Number of investors	0.002	0.187**
	(0.00)	(0.09)
Presence of professional investors	1.724**	6.862***
	(0.80)	(2.52)
Log min funding goal	1.127**	-6.076*
	(0.48)	(3.54)
constant	-10.459	39.702
	(6.51)	(30.12)
R2	0.20	
Pseudo-R2		0.89
AIC	785.15	24.74
BIC	803.01	42.60
N. of cases	145	145

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 4.24: Results of OLS and Logit models for hypothesis 3 testing

4.7 Discussion and conclusions

The transition from an experimental setting to real-world investment data open ups some interesting conclusions. The aim of this study was to confirm or reject hypothesis tested in a lab-experiment, where a necessary trade-off between internal and external validity is to be made (Loewenstein, 1999).

The research hypotheses concerned the effect of different sets of signals conveyed by various sources on the outcome of an ECF campaign. Indeed, signals propagate from different levels of a hypothetical information cascade to the crowd of investors. Less informed and unsophisticated investors might lack expertise, skills or miss relevant sets of information to evaluate a business project. As their prevalent purpose is of monetary nature, they opt for heuristics or shortcuts to pick the most promising projects. Above all, they are able to observe and learn from the signals conveyed. Especially in a FinTech setting, this is made possible thanks to a digital environment, where information and knowledge sharing is eased and catalyzed. Thus, they try to deal with it by replicating the decision making of others. Ultimately, herding happens whenever a group of investors act in a similar manner, suggesting the tendency of less-informed parties to mimic better-informed ones. As a result, the outcome of a campaign depends not only on the characteristics of a project, but also upon the behaviour of investors. On one hand, this means that good project quality is promoted, as the information might propagate among the information cascade, resulting in an efficient herd behavior. On the other hand, errors or simply information manipulations, if not verified, might end up in an incorrect pursuit of misleading information.

First, an exploratory by means of machine-learning and in particular classification algorithms was undertaken. The aim was to identify and assign features to a sub-sample of data and eventually to allow for subsequent more accurate analysis via econometric modeling. Indeed, the exploratory analysis of the ten platforms served not only to provide an overview of the phenomenon, but also to identify which categories an observation belongs to and gather a preliminary insight of the set of features identified with labelled successful campaigns upon which building the econometric analysis.

Second, a cross-sectional analysis (Panel A) was developed to test the effects of explanatory variables, representing different sets of signals, on both the amount of funding raised from investors and the outcome of an ECF campaign. Results from the econometric models show that a higher amount of capital raised is characterized by higher shares of equity offered to investors, higher pre-money valuations, higher percentage of capital raised, higher numbers of investors, online presence on social media but with lower number of accounts, geographical heterogeneity, higher funding targets and higher funding caps.

Success of a campaign, instead, is associated with higher shares of equity retained by entrepreneurs, lower pre-money valuations, higher number of investors, no online presence, but if any the higher number of accounts the better, lower funding goals and apparently male entrepreneurial teams (Crowdcube).

These findings confirm the ambiguous effect for equity retention obtained experimentally in the previous study of this thesis, thus partially rejecting hypothesis 1. Firms with larger equity shares offered to the shareholders are less likely to succeed, but if they reach the minimum target, they can collect more capital. Although it is in contrast with previous studies (Vismara, 2016), many alternative explanations can be given. Investors might not take on this source of information as a signal, as they believe that entrepreneurs might be subject to overconfidence bias and tend to be overoptimistic about their risk tolerance and business abilities (Singh, 2020). For Wald et al. (2019), crowd-investors do not only pursue monetary incentives, but their intrinsic motivation is also to be part of the project to receive personal gain. However, another explanation might take into consideration that unsophisticated investors do not have expertise to process financial metrics such as equity retention and adopt different (but not necessarily irrational) evaluation criteria than sophisticated investors (Lukkarinen et al., 2016).

Similarly, an ambiguous effect is also found for the pre-money valuation. Apparently, firms with higher evaluations from the experts are less likely to succeed, but in case they reach the target, they are able to attract larger amounts of capital. Hypothesis 2 is only partially supported. Apparently, when it comes to observing financial measures, crowd-investors seem to adopt different evaluation criteria (Lukkarinen et al., 2016). Previous literature on investor behaviour has found that investors tend to evaluate more heavily characteristics that are easier to understand. The "less-is-better effect" claims that individuals facing a high variety of information of different complexity might be subject to a cognitive distortion known as "evaluability heuristic" (Hsee, 1998).

With regards to hypothesis 3, the effect of the presence of more sophisticated investors appears to be significant for both concluding successfully a campaign and raising higher amounts of capital. Evidence supports hypothesis 3, in line with the previous experimental study.

Moreover, findings suggest that investors tend to bid preferably for projects already backed by a higher number of investors and showing a higher financial commitment from both the crowd and professional investors. Hypotheses 4 and 5 cannot be rejected and are then supported by evidence, resulting in line with previous literature (Vulkan et al., 2016). Late investors in fact seem to perceive early bids as a signal for the wisdom-of-the-crowd and might tend to assume a herd behaviour.

As far as social media network is concerned, ambiguous effects are found. On one hand investors appear to use social media to gather more information. On the other hand, they tend to do not give particular credit to the online presence or to the number of social media accounts owned by the entrepreneurs or the firm. Thus, hypotheses 6 is partially rejected.

Similarly, the geographical proximity appears not to be an effective signal, based on the Hofstede theory (Hofstede, 2011), capable of attracting more investments. On the contrary, although no significant effect is found on the outcome of a campaign, spatial distance is associated with more capital raised. In other words, individuals seem to invest beyond the mere geographical borders. Therefore, openness of new ventures (and ECF platforms) to foreign shareholders appear to guarantee wider access to equity and larger amounts of capital raised.

Third, allowing for time variability of observations, a panel-data analysis (Panel B) was developed to test dynamically the effects of information cascades on the behaviour of crowd-investor. The longitudinal analysis reports that investors tend to bid for projects that present a higher proportion of equity shared among internal shareholders, lower pre-money valuations proposed by advisors/analysts and backed by a wider crowd of investors and, particularly, by early investors.

Therefore, adding time-varying effects the effect of equity retention turns out to be significantly positive to obtain more financing. This result appears in contrast with both the cross-sectional findings and the experimental setting. However, it appears in line with previous literature (Vismara, 2016).

Similarly, the impact of evaluations of the business proposed by experts appears in contrast with the cross-sectional analysis and previous literature (Löher et al., 2018). Although not particularly strong, the variable presents a negative coefficient. Again, the motivations provided for the cross-sectional analysis seem suitable to address this finding.

As for hypotheses 4 and 5, panel-data analysis appears in line with the cross-sectional results and previous literature, reinforcing the theory of wisdom-of-the-crowd and herding effects.

In general, overall results from different empirical settings suggest that unsophisticated crowd-investors tend mainly to follow the "pack" and interpret positively and significantly signals received from the crowd. In particular, investors tend to act as "birds of a feather flock together" and early-bird investors have the capability of convincing late and undecided ones (Vismara, 2018). However, an important consideration has to be made. Due to its significant and strong impact, this signaling mechanism might also be used for bad practices and induce moral hazard. Indeed, entrepreneurs themselves or platform owners might manipulate this information cascade by making a non-confirmed bid during the campaign and withdraw the investment before the conclusion in order to attract late investors (Meoli and Vismara, 2021). Therefore, crowd-investors should be aware of bad practices and possibly verify whether investments are confirmed or not, as well as try not to rely only on this source of information.

As concluding remarks, the Covid-19 pandemic seems to have fostered investments in ECF. Results from the data scraped in between 2019 and 2020 showed an increment of the transactions, and significant impact on the amount of capital raised. This is probably due to the increment of digitalization and FinTech usage during lockdowns imposed by countries where the ECF campaigns were listed, as well as to the resilient adoption of more innovative and inclusive marketing and promoting means.

Appendix to chapter 4

Table 4.25: Panel A: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Capital raised∼R	1.000																		
(2) Campaign success	0.207***	1.000																	
(3) Equity retention	0.023	0.079*	1.000																
(4) Pre-money valu∼n	0.714***	0.100**	0.127***	1.000															
(5) Percentage of ∼d	0.349***	0.501***	0.081*	0.219***	1.000														
(6) Number of inve∼s	0.706***	0.203***	0.050	0.661***	0.406***	1.000													
(7) No. social media	-0.118**	0.181***	0.113**	-0.086*	0.260***	-0.071	1.000												
(8) Presence on so∼a	-0.019	0.200***	0.064	-0.041	0.288***	0.058	0.792***	1.000											
(9) Geographical p∼y	-0.048	-0.046	0.002	-0.069	0.011	-0.003	0.125**	0.035	1.000										
(10) Presence of p∼n	0.157*	0.906***	0.134*	-0.007	0.537***	0.194**	0.096	0.060		1.000									
(11) Covid period	-0.016	-0.015	-0.008	-0.010	0.028	0.032	-0.035	-0.059	0.019	0.075	1.000								
(12) Minimum inves∼t	0.788***	0.111**	-0.055	0.525***	0.032	0.513***	-0.196***	-0.126**	-0.044	-0.101	-0.066	1.000							
(13) Entrepreneur ∼y	0.159***	-0.008	0.117**	0.161***	0.037	0.087	-0.156***	-0.145**	-0.040		-0.068	0.197***	1.000						
(14) Firm age	0.239***	0.095*	0.072	0.172***	0.094*	0.175***	-0.135**	-0.128**	-0.024		-0.032	0.313***	0.768***	1.000					
(15) Entrepreneur ∼r	-0.048	-0.149***	-0.087*	-0.038	-0.125**	-0.041	-0.094*	-0.128***	-0.013	-0.117	-0.033	-0.019	0.124**	0.069	1.000				
(16) Entrepreneur ∼e	0.139**	0.072	0.040	0.113*	0.025	0.085	0.040	0.043	-0.009		0.054	0.164***	0.074	0.233***	-0.008	1.000			
(17) Price per share	-0.070	0.058	-0.006	-0.058	-0.038	-0.065	0.053	0.074	0.036	0.075	0.224**	-0.082	0.678**	0.554*	-0.044	0.170	1.000		
(18) Maximum inves∼t	0.524***	0.034	-0.377***	0.404***	0.098	0.475***	-0.235**	-0.032		0.031	-0.044	0.650***			-0.094		-0.042	1.000	
(19) Equity	0.029	0.024	-0.036	0.289***	-0.061	0.044	-0.226**	-0.312***		0.024	0.005	0.045			-0.058		-0.044	-0.024	1.000

*** p<0.01, ** p<0.05, * p<0.1

Table 4.26: Panel B: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Capital raised~R	1.000																
(2) Campaign success	0.242***	1.000															
(3) Equity retention	-0.078*	0.091**	1.000														
(4) Premoney valua~n	0.730***	0.180***	0.188***	1.000													
(5) Percentage rai~d	0.471***	0.444***	-0.009	0.414***	1.000												
(6) Number of inve~s	0.523***	0.263***	0.087**	0.832***	0.502***	1.000											
(7) No. social media	-0.045	0.043	0.172***	0.023	-0.053	-0.017	1.000										
(8) Presence socia~a	0.041	0.039	0.134***	0.036	0.001	0.043	0.490***	1.000									
(9) Geographical p~y	0.037	-0.035	-0.111**	-0.050	0.036	0.019	-0.165***	0.015	1.000								
(10) Min investmen~t	0.794***	0.168***	-0.220***	0.601***	0.095***	0.331***	0.002	0.063*	0.034	1.000							
(11) Interested in~s	0.911***	0.231***	0.139**	0.852***	0.684***	0.646***	-0.049	0.021	0.085	0.620***	1.000						
(12) Largest inves~t	0.861***	0.116*	-0.007	0.258***	0.426***	0.096*	0.005	0.027	-0.030	0.644***	0.751***	1.000					
(13) Remaining day~c	-0.158***	-0.246***	0.173***	0.014	-0.317***	-0.154***	0.083	0.031	-0.026	-0.063	-0.163***	-0.103*	1.000				
(14) Firm age	0.130**	0.069	0.050	0.047	0.150**	0.151**	0.096*	0.008	-0.047	0.258***	0.172***	0.062	-0.040	1.000			
(15) Entrepreneur ~r	-0.113*	-0.293***	0.106*	-0.070	-0.185***	-0.108*	-0.078	-0.091	0.033	-0.126**	-0.110*	-0.071	0.074	-0.168***	1.000		
(16) Entrepreneur ~e	0.204***	-0.049	0.182***	0.140**	0.045	0.168***	-0.028	-0.077	0.050	0.277***	0.195***	0.125**	-0.051	0.388***	0.102*	1.000	
(17) Entrepreneur ~y	0.006	-0.135**	0.063	0.005	-0.075	-0.052	0.179***	0.015	-0.152**	0.111*	-0.063	-0.010	-0.011	0.559***	0.082	0.138**	1.000

*** p<0.01, ** p<0.05, * p<0.1

References for Chapter 4

Agrawal, A., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy*, *24*(2), 253–274.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship theory and practice*, *39*(4), 955–980.

Alasadi, S. A., & Bhaya, W. S. (2017). Review of data preprocessing techniques in data mining. *Journal of Engineering and Applied Sciences*, *12*(16), 4102–4107.

Bandura, A., & Walters, R. H. (1977). *Social learning theory* (Vol. 1). Englewood cliffs Prentice Hall.

Barbi, M., & Mattioli, S. (2019). Human capital, investor trust, and equity crowdfunding. *Research in International Business and Finance*, *49*, 1–12.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2013). Individual crowdfunding practices. *Venture Capital*, *15*(4), 313–333.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy*, *100*(5), 992–1026.

Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff papers*, *47*(3), 279–310.

Blaseg, D., Cumming, D., & Koetter, M. (2021). Equity crowdfunding: High-quality or low-quality entrepreneurs? *Entrepreneurship Theory and Practice*, *45*(3), 505–530.

Block, J., Hornuf, L., & Moritz, A. (2018). Which updates during an equity crowdfunding campaign increase crowd participation? *Small Business Economics*, *50*(1), 3–27.

Breiman, L., Friedman, J., Olshen, R., & Stone, C. (n.d.). Classification and regression trees. 1984 monterey, ca wadsworth & brooks. *Cole Advanced Books & Software Google Scholar*.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, *37*(1), 39–67.

Courtney, C., Dutta, S., & Li, Y. (2017). Resolving information asymmetry: Signaling, endorsement, and crowdfunding success. *Entrepreneurship Theory and Practice*, *41*(2), 265–290.

Cover, T., & Hart, P. (1967). Nearest neighbor pattern classification. *IEEE transactions on information theory*, *13*(1), 21–27.

Cumming, D. J., Leboeuf, G., & Schwienbacher, A. (2020). Crowdfunding models: Keep-it-all vs. all-or-nothing. *Financial Management*, *49*(2), 331–360.

Dushnitsky, G., & Fitza, M. A. (2018). Are we missing the platforms for the crowd? comparing investment drivers across multiple crowdfunding platforms. *Journal of Business Venturing Insights*, *10*, e00100.

Endel, F., & Piringer, H. (2015). Data wrangling: Making data useful again. *IFAC-PapersOnLine*, *48*(1), 111–112.

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI magazine*, *17*(3), 37–37.

Fix, E., & Hodges, J. L. (1989). Discriminatory analysis. nonparametric discrimination: Consistency properties. *International Statistical Review/Revue Internationale de Statistique*, *57*(3), 238–247.

Freund, Y., & Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, *55*(1), 119–139.

Frid, C. J., Wyman, D. M., & Gartner, W. B. (2015). The influence of financial'skin in the game'on new venture creation. *Academy of Entrepreneurship Journal*, *21*(2), 1.

Hall, M. A. et al. (1999). Correlation-based feature selection for machine learning.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 1251–1271.

Hobey, E. (2015). Seeking industry transparency, companisto publishes its equity crowdfunding performance data, focusing on germany, austria and switzerland. *Crowdfund Insider*.

Hofstede, G. (2011). Dimensionalizing cultures: The hofstede model in context. *Online readings in psychology and culture*, *2*(1), 2307–0919.

Hornuf, L., & Schwienbacher, A. (2018). Market mechanisms and funding dynamics in equity crowdfunding. *Journal of Corporate Finance*, *50*, 556–574.

Hsee, C. K. (1998). Less is better: When low-value options are valued more highly than high-value options. *Journal of Behavioral Decision Making*, *11*(2), 107–121.

Kandel, S., Heer, J., Plaisant, C., Kennedy, J., Van Ham, F., Riche, N. H., Weaver, C., Lee, B., Brodbeck, D., & Buono, P. (2011). Research directions in data wrangling: Visualizations and transformations for usable and credible data. *Information Visualization*, *10*(4), 271–288.

Kleinert, S., & Volkmann, C. (2019). Equity crowdfunding and the role of investor discussion boards. *Venture Capital*, *21*(4), 327–352.

Leland, H. E., & Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. *The journal of Finance*, *32*(2), 371–387.

Loewenstein, G. (1999). Experimental economics from the vantage-point of behavioural economics. *The Economic Journal*, *109*(453), F25–F34.

Löher, J., Schneck, S., & Werner, A. (2018). A research note on entrepreneurs' financial commitment and crowdfunding success. *Venture Capital*, *20*(3), 309–322.

Lukkarinen, A., Teich, J. E., Wallenius, H., & Wallenius, J. (2016). Success drivers of online equity crowdfunding campaigns. *Decision Support Systems*, *87*, 26–38.

Meoli, M., & Vismara, S. (2021). Information manipulation in equity crowdfunding markets. *Journal of Corporate Finance*, *67*, 101866.

Nitani, M., Riding, A., & He, B. (2019). On equity crowdfunding: Investor rationality and success factors. *Venture Capital*, *21*(2-3), 243–272.

Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *The American economic review*, 465–479.

Signori, A., & Vismara, S. (2018). Does success bring success? the post-offering lives of equity-crowdfunded firms. *Journal of Corporate Finance*, *50*, 575–591.

Singh, R. P. (2020). Overconfidence: A common psychological attribute of entrepreneurs which leads to firm failure. *New England Journal of Entrepreneurship*.

Spence, M. (1973). L the mit press. *The Quarterly Journal of Economics*, *87*(3), 355–374.

Spence, M. (2002). Signaling in retrospect and the informational structure of markets. *American Economic Review*, *92*(3), 434–459.

Surowiecki, J. (2005). *The wisdom of crowds.* Anchor.

Vismara, S. (2016). Equity retention and social network theory in equity crowdfunding. *Small Business Economics*, *46*(4), 579–590.

Vismara, S. (2018). Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice*, *42*(3), 467–497.

Vrontis, D., Christofi, M., Battisti, E., & Graziano, E. A. (2020). Intellectual capital, knowledge sharing and equity crowdfunding. *Journal of Intellectual Capital*.

Vulkan, N., Åstebro, T., & Sierra, M. F. (2016). Equity crowdfunding: A new phenomena. *Journal of Business Venturing Insights*, *5*, 37–49.

Wald, A., Holmesland, M., & Efrat, K. (2019). It is not all about money: Obtaining additional benefits through equity crowdfunding. *The Journal of Entrepreneurship*, *28*(2), 270–294.

Welch, I. (1992). Sequential sales, learning, and cascades. *The Journal of finance*, *47*(2), 695–732.

Zhang, J., & Liu, P. (2012). Rational herding in microloan markets. *Management science*, *58*(5), 892–912.