Information preference in equity crowdfunding investment: the moderation of financial knowledge and digital agency

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Abstract

The reliability, speed, and breadth of digital financial information disseminated through equity crowdfunding (ECF) platforms make it important to understand the behaviors of non-professional and unqualified investors when they decide to finance a startup, a typically high-risk activity. This is reinforced by the fact that the "herding" behavior of ECF investors is a well-established way in which they tend to fill their gaps in knowledge, skills, and experience. A discrete choice experiment was administered during December 2022 to January 2023 to a sample of N=1,018 Italian households representative of Italian consumers and retail investors. The study analyzes their preferences toward different types of information that influence their decision making, presumably guiding their "herding" behavior. As expected, the results show that these individuals are most significantly influenced by public sources of information (the percentage of equity already paid by other investors and the number of social networks operated by the startup) and less by private ones (the number of professional investors and the value of the startup before the last funding round). In addition, the study highlights a moderating role of financial knowledge and digital agency. In fact, individuals with higher levels of financial literacy increase the perceived importance of the presence of financial professionals. The upscale is even higher for individuals who exhibit high levels of digital skills. This evidence is further proof of the importance of programs, both institutional and private, aimed at increasing levels of financial education and digital agency in a country.

JEL: G11; G14; G23; G24; G41

Keywords: Equity crowdfunding; private/public information; soft/hard information; herd behaviour; Discrete Choice Experiment; financial knowledge; digital agency; financial commitment.

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1. Introduction

The digitization of finance implies transformations in both the demand side of capital and the supply side. Fintech solutions, an expression of these transformations, accelerate financial disintermediation with the development of digital venues through which capital can flow. Equity crowdfunding (ECF) is an example of these venues, and it has developed because it is particularly suited to a type of capital seekers, toward whom the greatest fear of adverse selection by classical lenders (the banks, the stock exchanges) is concentrated.

However, digital solutions do not eliminate the real problem of capital exchange, which lies in the intensity and forms of risk transferred from the demand side to the supply side of capital markets. Classical finance paradigms pose the problem of how information should unambiguously convey the risk transferred from borrowers to lenders, that is, from funded entrepreneurs to investors. This

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[1] The ideas and positions in the paper are personal views of the authors and cannot be attributable to Consob.

riskiness is highest in startups, which by their nature have a low (or absent) track record and focus on innovative activities.

This increased riskiness, paradoxically, cannot be expected to be matched by a corresponding (and desirable) increased risk-bearing capacity on the part of investors. In the case of ECF, in fact, the nature of the investment, which is generally small in amount and highly accessible precisely because of digitization, identifies the type of investor with the expression "crowd," that is, investor of modest size, not characterized by marked financial or economic expertise in general. The expression "crowd-funding" itself would seem to emphasize the characterizing element of the operation, namely the financing offered by the "crowd," as opposed logically to what "professional financing" might be.

Thus, in the context of the ECF, the democratization of access to capital has introduced a new dimension to investment decisions, allowing, on the one hand, startups and small businesses to raise funds from a diverse pool of investors. On the other, investors now have direct access to a wide range of business ventures, avoiding traditional intermediaries. This paradigm shift requires an exploration of how retail investors navigate this new information environment to inform their investment decisions (Hornuf and Schwienbacher, 2018) and guide their perceptions of risk.

The solution to this paradox is the reliability, speed, and breath of information being conveyed by financial market offerings and competitions enabled by digitization.

This paper explores the preferences of individuals toward different types of information that influence their decision making, namely, on the one hand, public information elements (the percentage of equity already paid by other investors, the number of social networks operated by the startup, and the number of retail investors already involved in the campaign), and on the other hand, proxies from private sources (the pre-money valuation of the startup by analysts and the presence of professional investors). In addition, this study investigates whether these preferences are influenced by individuals' levels of financial and digital knowledge. To this end, a discrete choice experiment was administered to a sample of N=1,018 Italian households representative of Italian consumers and retail investors.

The structure of the paper is as follows. In section 2, the theoretical background delves into the economic value of information, with a specific focus on how information is perceived and valued by retail investors, its role in shaping investment preferences, and the distinction between private and public information. Section 3 develops the conceptual model of the research and Section 4 the methodology adopted. Section 5 describes the sample and key summary statistics of the dataset. Section 6 presents the results of the model estimates. Finally, Sections 7 and 8 discuss the main results and conclude the paper.

2. Theoretical background in retail investment decision-making process

2.1. Economic value of information: private vs public information

The economic landscape has undergone significant transformations in recent years, driven by the growing importance of information in decision-making processes and the increasing speed of information sharing thanks to the digital ecosystem (Thakor, 2020). Information is recognized as a critical asset that can influence economic activities and outcomes, particularly in the field of investment and finance, where adverse selection and risk are around the corner. Adverse selection refers to the presence of information asymmetry, where one party possesses more information than the other, leading to potential market distortions (Cassar, 2004) and, ultimately, the financing of less promising ventures (Akerlof, 1970; Carpenter and Petersen, 2002). The management and mitigation of risks, both systematic and idiosyncratic, is critical to sustaining a stable and resilient financial environment. This is especially true for alternative financial markets based on FinTech and digital innovations (Blaseg et al., 2021).

Retail investors, which include individual agents who usually possess less investment experience and skills than institutional and professional investors, play a significant role in innovative financial markets such as the ECF. Previous research has shown that retail investors follow different decision-making dynamics than professional investors (Vismara, 2019). In fact, their investment decisions are influenced by a different set of information, including news, analyst reports, entrepreneurs' behavior, investor crowd behavior, and social media sentiment - in other words, community logic. Professional investors, on the other hand, are driven by market logic (Vismara, 2019). Moreover, the ECF is based on a FinTech ecosystem, where information flows rapidly and publicly across a digital landscape (Goldfarb & Tucker, 2019).

Understanding the types of information that retail investors evaluate to choose the most promising ECF projects is critical to understanding their financing decisions. Unlike professional investors, retail investors often rely on information that is easily accessible, understandable, and in line with their investment objectives and risk tolerance (Hsee, 1998). In other words, decision makers faced with a high variety and complexity of information tend to evaluate more heavily the more easily understood features, following the so-called "evaluability heuristic" and the "less is more" effect. Indeed, behavioral finance theories argue that investors' decisions are not purely rational, but are influenced by psychological factors (Baltussen, 2009).

In addition, retail investors, especially those without specialized experience/knowledge, are known to be prone to a range of cognitive distortions (Kahneman and Tversky, 1974, Baltussen, 2009) and limited rationality (Camerer, 1998), prone to fallacious evaluations (Ahlers et al., 2015; Hornuf and Schwienbacher, 2014). Therefore, they are prone to alleviate the complexity of their decisions through the use of thinking shortcuts (heuristics) in order to reach satisfactory solutions (Simon, 1955). The decision to invest or not to invest, precisely because of the small size of financial investments in ECFs, makes it plausible that it is purely individual and hardly assisted by outside advisors. Retail investors, left to make decisions on their own, lacking sufficient skills and experience to assess investment prospects, incur high monitoring costs (Ahlers et al., 2015; Cumming et al., 2019); they therefore implement practical methods, even traceable to heuristic procedures, to improve their choice process under conditions of information asymmetry and limited rationality, trying to acquire as much information as possible, both technical-financial and by following the behavior of economic agents who are assumed to possess private and broader information sets. This phenomenon is often referred to as the "herd effect" (Scharfstein and Stein, 1990) and describes the tendency of individuals to mimic the behavior of a group. In this way, they gain an economic advantage from the aggregation of individual information learned from others (Grossman and Stiglitz, 1976), aligning their own choices and beliefs with those of traders deemed more informed (Bikhchandani et al., 2001). This feature of retail investment decision making is therefore particularly relevant for investors in ECFs.

2.2.Dissemination of digital financial information in financial markets

The advent of digital technologies has revolutionized the spectrum of technologies, empowering investors with real-time information and analytical capabilities. The ability of an individual to control and adapt to a digital world is defined as digital agency (Passey et al., 2018, p. 426). It is a broader concept that comprehends the capacity to engage with technology in a 'meaningful' and 'capital-enhancing' way (Pearce and Rice, 2017; Siddiq et al., 2023).

Digital agency, encompassing digital competence, digital confidence, and digital accountability, plays a pivotal role in shaping the investment decisions of retail participants (Passey et al., 2018). Digital competence involves the ability to comprehend and utilize digital financial information safely and effectively, embracing both digital skills and literacy.

Concurrently, digital confidence refers to the adeptness in utilizing digital tools and, in particular, confidence in applying digital competence in everyday situations. In other words, it reflects the ability to use digital tools, such as the internet and other applications or software, autonomously, expertly, and in different contexts. For financial decision-making, retail investors who demonstrate digital confidence and digital-savvy behaviors leverage technological resources to assess risks, explore investment opportunities, evaluate different sources of information, and engage with the dynamic crowdfunding ecosystem.

Digital accountability involves responsible and conscious behavior in the digital world. In the ECF context, it reflects the use of digital financial information and platforms, ensuring ethical and transparent investment practices in the digital realm.

2.3. Hard vs soft information in ECF

This study also draws upon the theoretical framework that categorizes information into hard and soft (Petersen, 2004; Liberti and Petersen, 2018). Hard information pertains to verifiable facts with widespread consensus, typically resistant to alteration during the investment period. Conversely, soft information is dynamic, changeable, and susceptible to diverse interpretations and challenges in verification (Bertomeu & Marinovic, 2016; Liberti & Petersen, 2018).

In the realm of ECF, digital platforms present a transformative opportunity by potentially mitigating the transaction costs associated with acquiring, disseminating, and interpreting information, including soft information (Goldfarb & Tucker, 2019). Indeed, the architecture of ECF platforms, characterized by open access, encourages entrepreneurs to disclose a wealth of information, fostering an environment where hard facts and high-quality soft information are shared at scale. Additionally, the informational landscape in ECF is subject to constant updates, revisions, and reinterpretations, emphasizing the fluidity of the latter. This democratized information flow benefits both entrepreneurs and investors, allowing for a more informed decision-making process (Estrin et al., 2021).

3. Conceptual model

According to EU Regulation 2020/1503, an investor is defined as "unsophisticated" if they have an annual gross personal income of less than €60,000 or hold investment portfolios of less than €100,000, lack proven experience (including work experience) in the financial world, or have made major financial transactions in the last period (an average frequency of 10 transactions per quarter in the previous four quarters).

We assume that in the context of ECF, the financing offered by the "crowd" of unsophisticated (retail) investors follows different decision-making logics from those of professional and sophisticated investors in forming their beliefs about investment projects (Vismara, 2019).

As anticipated in previous sections, in financial markets, information is often classified dichotomously into private and public information. Private information refers to data known to a select few, introducing information asymmetry and providing a competitive advantage to those who possess it. Public information, on the other hand, is widely available and known to all market participants, depending on how quickly it is disseminated (Morris and Shin, 2002).

In the ECF context, public information is disseminated through crowdfunding platforms and other accessible channels, e.g., social media. The efficient selection of promising investments relies on the assimilation and interpretation of both private and public information, reflecting also the aggregate knowledge of market participants. Additionally, information that could be exploited in the ECF investment decision-making process may also be distinguished between hard and soft information.

Keeping in mind that investors in ECF are more likely to make a decision through herding available information (i.e., public information), constructing knowledge that is called the 'wisdom of the crowd' (Polzin et al., 2017), and also soft information (Estrin et al., 2021), the first hypothesis of the paper can be formulated as follows:

H1: *Economic value and the nature of the information source determine the investment preferences of retail investors.*

> **H1a:** *Retail investors tend to consult sources of information that are public rather than private ones.*
>
> **H1b:** *Retail investors tend to consult sources of information that are soft rather than hard ones.*

We know from the literature (Weick, 1995) that financial knowledge is a key element in the process of information evaluation by retail investors, with a profound impact on their ability to discern, interpret, and act on financial and non-financial information. Financially literate retail investors are better equipped to critically evaluate information sources and assess their credibility and relevance, thus discerning the signal from the noise. A higher level of financial knowledge enables them to make well-informed investment decisions and navigate the complex financial terrain with confidence (Yang et al., 2023; van Rooij et al., 2011).

Therefore, we argue that the role of moderation played by financial knowledge is evident, as demonstrated by the tendency of skilled retail investors to consider the sources of private information with more attention. This implies the second hypothesis of this paper:

> **H2:** *Retail investors with high financial knowledge tend to consult sources of private information.*

The speed at which information circulates in the digital age has profound implications for retail investors participating in ECF. The velocity of information dissemination is accelerated by online platforms, social media, and digital communication channels, creating an environment where news and real-time updates swiftly reach a wide audience. This rapid dissemination has a direct impact on investors' decisions, requiring them to rapidly incorporate new information into their decision-making processes. Quick access to information means that retail investors must adeptly process and incorporate new developments into their investment decisions in real-time. This introduces the third hypothesis of this paper:

> **H3:** *Retail investors with high digital agency tend to consult sources of private information.*

To test our conceptual framework (Figure 1), the case of Italian ECF marketplace is explored, considering it significantly developed in terms of business (1,325 fundraising campaigns launched, of which 81.4% closed successfully, and €571,680,000 of capital raised; Politecnico di Milano, 2023), regulations (in 2013, Italy became the first country in Europe to have specific discipline on crowdfunding[2]; CONSOB regulation 18592/2013) and ECF platforms (48 authorized platforms by the CONSOB[3]; Politecnico di Milano, 2023).

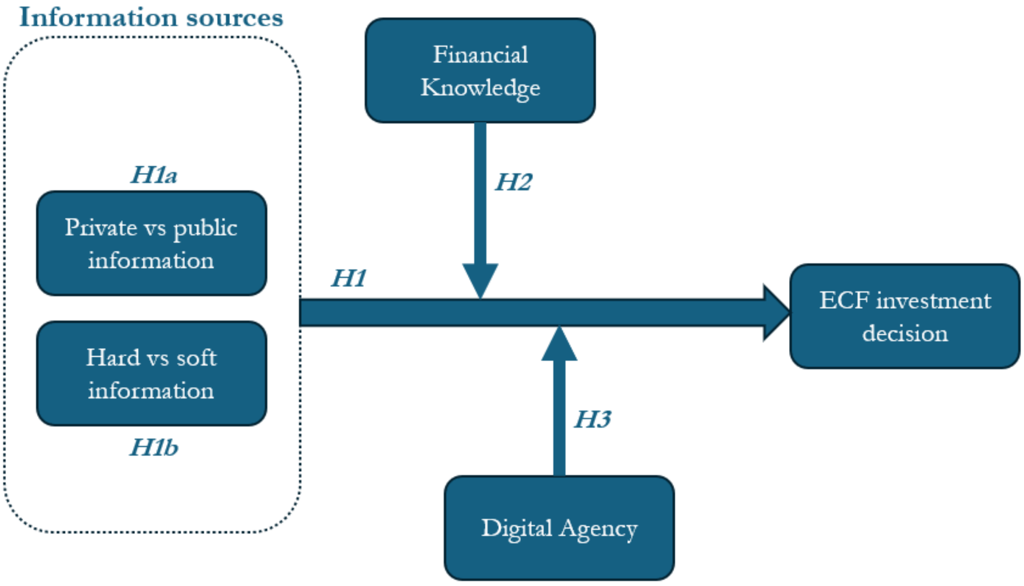


Figure 1 conceptual model

4. Methodology

4.1. The Discrete Choice Experiment (DCE)

Discrete Choice Experiments constitute a quantitative research method useful for estimating individuals' subjective preferences and understanding the factors that influence their decision-making (Train, 2003). A DCE is based on an indirect method of preference detection, in which individuals are not required to provide an absolute measure of the utility associated with a choice. Instead, they express a preference among hypothetical alternatives through a series of choice scenarios (Ali and Ronaldson, 2012). Methodologically, a choice experiment requires defining the attributes that can influence preferences, determining the levels for each attribute, and creating the choice scenarios (choice set).

4.2. Attributes of the experiment

The *attributes* of the choice alternatives elicited in this paper reconcile the conceptual framework of the paper with the information effectively available on the web campaigns presented by the Italian ECF platforms, representing the various sources of information that a potential retail investor may consult. This also reflects the reliability of the information available and requested by the platforms. As a result, the attributes considered are as follows:

[2] This study precedes the implementation in Italy of the Regulation on European Crowdfunding Service Providers (ECSP) for business (EU) 2020/1503.

[3] See the previous note.

- percentage of company share distributed to future members (investors/shareholders) in case of achievement of the raising campaign (%EQUITY-OFFERED);[4]
- presence of a link to an active social profile of the startup on Facebook/ Instagram/ Twitter (X)/ LinkedIn (SOCIALS);
- pre-money value in Euros of the startup estimated by analysts and advisors prior to launching the equity crowdfunding campaign ($PRE-MONEY);
- percentage of investment confirmed (paid) by investors (%INVEST-CONFIRMED);
- number of professional investors present, such as business angels, venture capital, financial intermediaries (N-PROF-INVESTORS);
- number of retail investors present (N-RET-INVESTORS).

Therefore, as shown in Table 1, these six attributes, derived from the real-world context of Italian ECF platforms, are associated with their plausible nature of private/public information on one hand, and hard/soft information on the other hand.

Table 1 Empirical attributes and conceptual frame

		Economic value of the information	
		Public	**Private**
Nature	**Hard information**	SOCIALS	% EQUITY-OFFERED $PRE-MONEY
	Soft Information	%INVEST-CONFIRM N-RET-INVESTORS	N-PROF-INVESTORS

4.3.Levels of attributes

Then, the definition of the *levels*, similar to the elicitation of the attributes, was based on empirical evidence emerging from web campaigns to represent plausible investment choices consistent with the Italian market (Coast et al., 2007). Coherently, data collection via web scraping was conducted on the main Italian platforms, selecting those with values above the fiftieth percentile for the number of campaigns published and the amount of capital raised. From the ten Italian platforms identified, those operating exclusively in the real estate sector (i.e., Concrete Investing, Walliance) were excluded. Therefore, eight platforms are analyzed: 200Crowd, Backtowork24, CrowdFundMe, Doorway, MamaCrowd, Opstart, StarsUp, WeAreStarting.

A series of web scraping and data mining algorithms then extracted attribute reference information for each campaign. For each attribute, three levels (i.e., minimum, median, and maximum) were identified from the statistics of the platforms consulted, excluding outliers. Each attribute was then defined by dummy coding with three levels, with the exception of social media. The latter attribute was created as a categorical variable related to the number of social media visible in web campaigns (zero, two, or four socials).

The number of attributes and levels of each attribute is not random and results from a trade-off between the information obtainable from the experiment and the cognitive load required of participants (Mangham et al., 2009; Johnson et al., 2013). These factors, in fact, influence the number of choices participants are subjected to according to the formula:

[4] Equity offered is the complementary to 1 of equity retention.

$$(1)\quad cs = l\text{-}k+1$$

where cs is the number of choice set, l is the number of levels and k is the number of attributes. Therefore, with 19 total levels and six attributes, the expected number of choice scenarios is 14. Table 2 provides a summary of the levels by attribute considered in our DCE.

Table 2 Levels of the DCE by attribute

Attribute	*Levels*
% EQUITY-OFFERED	2% 9% 85%
SOCIALS	Nessuno (Facebook + Instagram) (Twitter (X) + LinkedIn) (Facebook + Instagram + Twitter (X) + Linkedin)
$PRE-MONEY	1,000€ 10,000€ 2,000,000€
%INVEST-CONFIRM	0% 88% 100%
N-PROF-INVESTORS	0 1 5
N-RET-INVESTORS	16 122 355

4.4.The choice sets of the experiment

Each choice set consists of two choice alternatives and one no-choice option, obtained by combining the attribute levels. This process results in the experimental design of a Discrete Choice Experiment (DCE), yielding a matrix of values where attribute levels are in the columns and choice alternatives are in the rows (Huber & Zwerina, 1996). This study opted for generating a D-efficient experimental design using a specific program developed in the R language: idefix (Traets et al., 2020). The program, based on inputs following the DCE design and relying on the Coordinate-Exchange Algorithm (CEA; Pérez-Troncoso, 2020), generated a design matrix containing fourteen choice sets.

Additionally, the obtained experimental design matrix must be interpreted and decoded to associate the values of the levels of each attribute with the choice alternatives and obtain the choice sets. This step was also developed in the R language with a special function in the idefix package. The alternatives obtained from the generation of choice sets present optimal combinations of attributes and levels that represent purely hypothetical investment solutions and may not necessarily have economic significance. In fact, the key to interpreting a DCE does not lie in the actual choice of a specific alternative but rather in how the choice is oriented based on the presence of certain levels of the attributes. For this reason, alternatives, having no specific parameters (alternative-specific), are "unlabeled" and referred to as "alternative A" or "alternative B."

While observing the sequence of the 14 choice sets, it may happen that certain levels are repeated more frequently than others; usually, an efficient experimental design possesses the property of balancing attributes and levels (Szinay et al., 2021). However, attempting to seek a perfect balance between attributes and levels and constraining it may result in suboptimal designs. Therefore, it was decided not to impose this additional constraint to avoid forcing the optimization proposed by the generative algorithm.

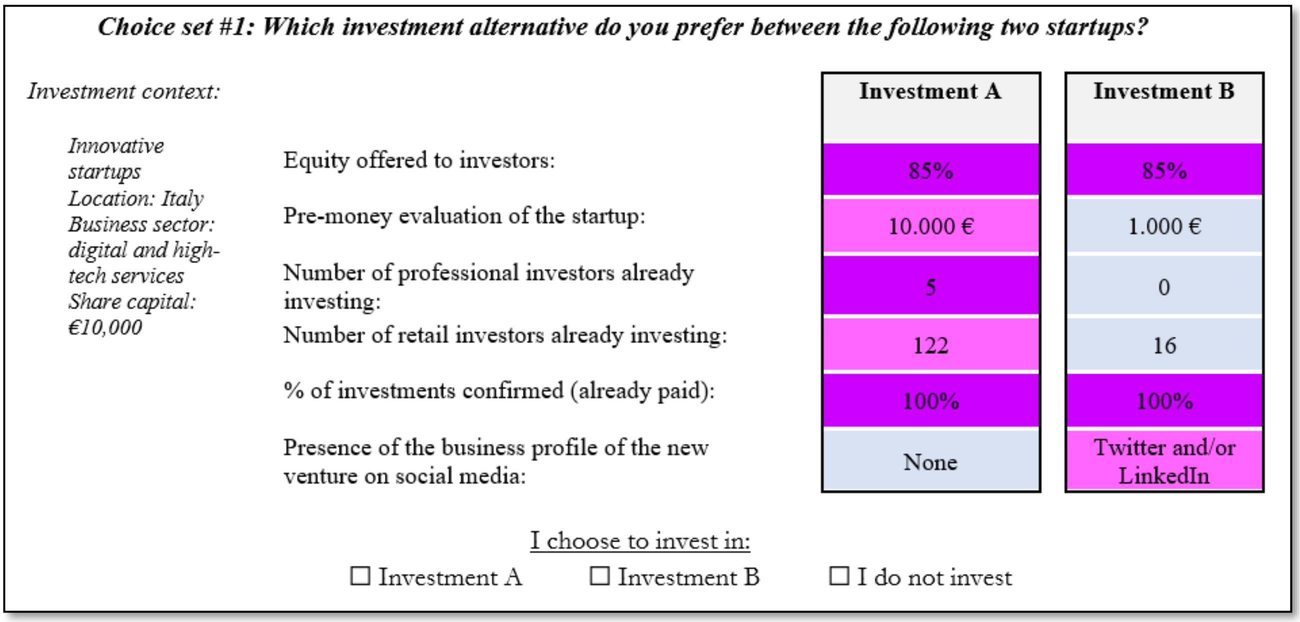
Finally, to guide the participants' choices, the context of the ECF investments was based on innovative startups requesting financial capital through equity crowdfunding, starting with a share capital of €10,000, based in Italy and operating in the digital and technology (high-tech) sector.

4.5.The on line survey

The choice experiment is presented in the form of an online survey, through which sociodemographic information about the participants is also collected, along with a set of questions on financial literacy and attitudes toward digitization. To reduce the cognitive overload of participation in the choice exercise and thus minimize possible response bias, three techniques were adopted.

First, two alternatives within the same choice scenario were allowed to have some attributes with the same level (attribute level overlap) to focus participants' attention on certain attributes, reducing the complexity of their task and improving the effectiveness of the experiment (Jonker et al., 2018).

The second technique involved the use of colors to highlight differences in levels between alternatives. Specifically, a scale of purple and grey was adopted to emphasize the maximum (dark purple) and minimum (light grey) levels within the same attribute (Jonker et al., 2018). The color choice is guided by the fact that these are colors that can be distinguished even by subjects with color blindness (Figure 2).



Choice set #1: Which investment alternative do you prefer between the following two startups?

Investment context:

Innovative startups
Location: Italy
Business sector: digital and high-tech services
Share capital: €10,000

	Investment A	Investment B
Equity offered to investors:	85%	85%
Pre-money evaluation of the startup:	10.000 €	1.000 €
Number of professional investors already investing:	5	0
Number of retail investors already investing:	122	16
% of investments confirmed (already paid):	100%	100%
Presence of the business profile of the new venture on social media:	None	Twitter and/or LinkedIn

I choose to invest in:

☐ Investment A ☐ Investment B ☐ I do not invest

Figure 2 Graphical representation of a choice set

Finally, the 14 choice sets, resulting from the experimental design, were divided into two blocks of seven each (blocking), which were alternately and randomly submitted to participants. Each participant was then randomly assigned to one of the two sub-samples (leg 1 or 2) and underwent the final survey, where seven choice scenarios were provided instead of 14.

4.6.Model specification

The *Conditional Logit* (McFadden, 1974) is one of the first models developed to analyze discrete choices. It is based on the assumption that individual preferences are constant across alternatives, and the only variations arise from differences in the characteristics of the alternatives themselves. The probability that an individual will choose alternative j among J possible alternatives is modeled through the expression:

$$(2)\ \Pr(choice = j) = \frac{\exp(V_{ij})}{\sum_{j=1}^{J} \exp(V_{ij})} \qquad ,$$

where Vij represents the estimated utility for alternative j by individual i, and the denominator the sum of estimated utilities for all alternatives.

5. The sample

Preliminary, an online pilot test was conducted via Google Forms during the period of October 2022 to assess participants' understanding of the tasks and interface, as well as to identify any technical problems or ambiguities in the questions. At the end of the pilot test, a short questionnaire was administered to participants to collect comments or suggestions on the clarity of the tasks assigned in the survey. The data collected at this stage were examined to assess the distribution of responses and the effectiveness of the selected questions. Descriptive statistics were calculated for the choices made by the participants, and any discrepancies or anomalies in the data were examined.

The final sampling and the administration of the full experiment were conducted in the period of December 2022 to January 2023 by the market analysis company GfK Italia. The target population sampled includes Italian household heads recalled from the July 2022 survey (CONSOB Report, 2023) and represents the Italian consumer and retail investor panel. It is important to note that the sampled subjects were not necessarily required to know about equity crowdfunding or have had previous investment experience, so as not to bias the sample by making it subject to survivorship bias.

The administration of the survey and experiment was conducted by GfK, which provided its own digital space on which to host the survey and invite participants to complete the experiment for a reward (reward).

The final sample of individuals surveyed is N=1,018, which exceeds the minimum threshold needed to estimate a DCE (Johnson and Orme, 1996):

$$(3) \qquad n \geq \frac{500 \cdot k}{cs \cdot a}$$

Where n is the number of participants, cs the number of choice sets, a the number of alternatives per choice set (excluding the status quo option), and k the maximum number of levels per single attribute.

Table 3 presents the characteristics of the sample population, offering a nuanced understanding of the demographic and socio-economic composition of the study participants. The dataset includes information from 1,018 individuals, providing insights into their age distribution, gender composition, geographical location, town size, educational background, and professional roles. The mean age of the participants is 52.47 years, with a standard deviation of 11.24, ranging from 22 to 75 years. The gender distribution indicates that 79.5% of the participants are male, while 20.5% are female.

Geographically, the majority of participants are from the South and islands region (36.1%) of Italy, followed by the Northwest (34%), Center (14.6%), and Northeast (15.3%). Town size diversity is represented, ranging from fewer than 5000 residents (14.2%) to over 500,000 residents (12.2%). Educational backgrounds vary, with the majority having a high school diploma (45.9%), and a significant proportion holding a university degree (32%). Professional roles encompass a wide range, including office workers or service persons (31.1%), retirees (18.3%), and individuals identifying as students (1%).

Table 3 Socio-demographic descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	1018	52.466	11.238	22	75
Gender composition	.	.	.	.	.
Male	1018	.795	.404	0	1
Female	1018	.205	.404	0	1
Geographical location	.	.	.	.	.
North west	1018	.34	.474	0	1
North east	1018	.153	.36	0	1
Center	1018	.146	.354	0	1
South and islands	1018	.361	.48	0	1
Town size	.	.	.	.	.
< 5000	1018	.142	.35	0	1
5000-10000	1018	.108	.311	0	1
10000-30000	1018	.27	.444	0	1
30000-100000	1018	.231	.422	0	1
100000-500000	1018	.127	.333	0	1
>500000	1018	.122	.327	0	1
Educational background	.	.	.	.	.
No education	1018	.001	.031	0	1
Primary school with diploma	1018	.004	.063	0	1
Middle school without diploma	1018	.001	.031	0	1
Middle school with diploma	1018	.105	.307	0	1
High school without diploma	1018	.032	.177	0	1
High school diploma	1018	.459	.499	0	1
University without degree	1018	.078	.268	0	1
University degree	1018	.32	.467	0	1
Professional roles	.	.	.	.	.
Student	1018	.01	.099	0	1
Homemaker	1018	.02	.139	0	1
Retired	1018	.183	.387	0	1
Looking for first job	1018	.012	.108	0	1
Looking for job	1018	.028	.164	0	1
Executive	1018	.015	.121	0	1
Middle manager	1018	.06	.237	0	1
Office worker or serviceperson	1018	.311	.463	0	1
Teacher	1018	.044	.206	0	1
Worker shop assistant employed farmer or apprentice	1018	.189	.391	0	1
Entrepreneur	1018	.021	.142	0	1
Freelancer with employees	1018	.005	.07	0	1
Freelancer with no employees	1018	.058	.234	0	1
Trader farmer craftsman with employees	1018	.015	.121	0	1
Trader farmer craftsman without employees	1018	.014	.117	0	1
Helper employee	1018	.004	.063	0	1
Others	1018	.014	.117	0	1

5.1. Summary statistics

In addition to the choice experiment attribute variables, moderation variables measuring the participants' level of financial knowledge and digital agency were included (Table **4**), based on the CONSOB Report (2023).

This study operationalizes financial knowledge using the "Big Five" questions developed by Lusardi and Mitchell (2014), where participants are assigned a score ranging from 0 to 5 based on their responses. Additionally, a dichotomous variable was introduced, termed "Dummy financial knowledge," which takes on a value of 1 if an individual scores above or equal to the median on the Big Five questions, and 0 otherwise.

Turning to digital competence, this construct is measured through questions in line with the OECD (2022), resulting in scores ranging from 0 to 7. Digital-savvy behavior, an essential aspect of digital agency, is gauged through questions inspired by the OECD (2022), yielding scores within the range of 0 to 7. Digital confidence is assessed by questions pertaining to digital and internet usage, also drawn from the OECD (2022), with scores ranging from 0 to 15.

Then, a comprehensive measure termed "Digital agency" is derived as the weighted mean of scores obtained on digital competence, digital-savvy behavior, and digital confidence, with values ranging from 0 to 1. To further categorize individuals, a dichotomous variable, "Dummy digital agency," is introduced, taking on a value of 1 if an individual's Digital Agency score is above or equal to the median, and 0 otherwise.

Table 4 Moderating variables description

Variable	*Description*	*Values*
Financial knowledge	Score obtained on “Big Five” questions on financial knowledge (Lusardi and Mitchell, 2014)	0-5
Dummy financial knowledge	A dichotomous variable =1 if the individual scored above or equal to the median on the Big Five questions on financial knowledge; =0 otherwise	0;1
Digital competence	Score obtained on questions relating digital competence and skills (OECD, 2022; CONSOB, 2023)	0-7
Digital savvy behaviour	Score obtained on questions relating digital savvy behaviour and accountability (OECD, 2022; CONSOB, 2023)	0-7
Digital confidence	Score obtained on questions relating digital and internet usage (OECD, 2022; CONSOB, 2023)	0-15
Digital agency	Weighted mean of the scores obtained on digital competence, digital savvy behaviour and digital confidence.	0-1
Dummy digital agency	A dichotomous variable =1 for values of the Digital Agency above or equal to the median; =0 otherwise	0;1

Table 5 summarizes key statistics related to financial knowledge and digital agency among the 1018 participants in our study. For financial knowledge, participants scored an average of 3.147 out of 5, with a standard deviation of 1.780, indicating moderate variability in scores. The distribution is skewed (-0.471) and exhibits positive kurtosis (1.804). The t-value of 56.401 is highly significant, suggesting a substantial difference in financial knowledge scores. The corresponding dummy variable for financial knowledge indicates that approximately 63.8% of participants scored above or equal to the median, with a standard deviation of 0.481 and a significant t-value of 42.293. Turning to digital competencies, participants scored an average of 3.682 out of 7, displaying moderate variability (SD = 2.059). Digital savvy behavior and confidence also reveal noteworthy statistics, with average scores of 4.775 and 4.674, respectively. The digital agency, representing the combined effect of digital competence, savvy behaviour and confidence, exhibits an average score of 0.507, suggesting a moderate level of engagement and providing insights into participants' capabilities in these domains. The DV for digital agency shows that, on average, 51.1% of participants score above the median.

Table 5: summary statistics of moderating variables

	N	Mean	SD	Min	Max	p25	Median	p75	Skewness	Kurtosis	t-value
Financial knowledge	1018	3.147	1.780	0	5	2	4	5	-.471	1.804	56.401
DV fin. knowledge	1018	.638	0.481	0	1	0	1	1	-.572	1.327	42.293
Digital competence	1018	3.682	2.059	0	7	2	4	5	-.448	2.126	57.043
Digital savvy behav.	1018	4.775	2.082	0	7	4	5	7	-.76	2.607	73.184
Digital confidence	1018	4.674	3.506	0	15	1	4	7	.698	2.757	42.53
Digital agency	1018	.507	0.210	0	1	.371	.54	.66	-.472	2.677	76.971
DV digital agency	1018	.511	0.500	0	1	0	1	1	-.043	1.002	32.587

Additionally, individuals with a low financial knowledge (369) presented an average age of 49.9, with a standard deviation of 10.929. The gender distribution in this sub-group indicates that approximately 21.4% are female. In contrast, the sub-group of those with a high financial knowledge score of 1 consisted of elder individuals (649) with an average age is 53.9 and a standard deviation of 11.165. The gender distribution in this sub-group indicates that approximately 20% are female.

The difference in mean ages between the sub-group of low financial knowledge and the sub-group of high financial knowledge is -3.97 (SD=0.72) years and significant (Two-sample t-test), indicating that, on average, individuals with a higher financial knowledge score are elder than those with a lower financial knowledge.

Furthermore, individuals with a low digital agency (498) presented an average age of 52.2, with a standard deviation of 11.626, ranging from 22 to 75 years. The gender distribution in this sub-group indicates that approximately 18.9% are females. The sub-group of individuals with a high digital agency consists of 520 participants, with an average age of 52.7 and a standard deviation of 10.859. The gender distribution in this sub-group indicates that approximately 22.1% are females. However, the t-test results suggest that there is no significant difference in mean scores between the sub-groups of low digital agency and high digital agency.

Table 6 show that the correlation coefficient between financial knowledge and digital agency is 0.398.

Table 6 Pairwise correlations FK - DA

Variables	(1)	(2)
(1) Financial Knowledge	1.000	
(2) Digital agency	0.398*	1.000

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

6. Results

6.1. Full model

First, the impact of the attributes' levels on the willingness-to-invest of retail investors is estimated with a conditional logit model. The results from the regression are reported in Table 7.

Starting with the equity offered attribute, the findings show that retail investors tend to prefer to invest in fundraising campaigns that offer a higher equity share to the crowd (85%) than a campaign in which entrepreneurs retain most of the shares for themselves (2%), with a highly significant coefficient (P-value < 0.01) of b=-0.266.

Considering the new venture's pre-money valuation, investors showed a weakly significant preference for higher valuations (2,000,000 €) than small companies valued at €1,000 by analysts before the fundraising campaign was launched (with an average b=-0.100 and s.e.=0.06 for the lower level).

Focusing on the other attributes, individuals showed a significantly strong willingness to invest in alternatives in which a large number of professional investors (at least 5) had already invested (average b=-0.307 and s.e.=0.05). Similarly, their investment preference is driven by campaigns in which more crowd-investors (355; or at least 122) bid (average b=-0.275 and s.e.=0.05).

Analyzing the crowd financial commitment, retail investors face a strong and significant increase in their willingness-to-invest for campaigns where at least 88% (but preferably 100%; with an average b=-0.713 and s.e.=0.05) of bids are confirmed.

Table 7: baseline estimation model

		(1) Full model Coef./(Std. err.)
	Y=choice	
	Status-quo	-0.620***
		(0.08)
% EQUITY-OFFERED	2% offered	-0.266***
		(0.06)
	9% offered	-0.002
		(0.05)
$PRE-MONEY	1.000€ premoney	-0.100*
		(0.06)
	10.000€ premoney	0.057
		(0.06)
N-PROF-INVESTORS	0 professional investors	-0.307***
		(0.05)
	1 professional investors	-0.143***
		(0.05)
N-RET-INVESTORS	16 retail investors	-0.275***
		(0.05)
	122 retail investors	-0.057
		(0.06)
%INVEST-CONFIRM	0% confirmed	-0.713***
		(0.05)
	88% confirmed	-0.049
		(0.05)
SOCIALS	None	-0.384***
		(0.05)
	Twitter (X) and/or LinkedIn	-0.239***
		(0.06)
	Facebook and/or Instagram	-0.156**
		(0.06)
	N	1018
	Pseudo R-squared	0.04
	AIC	14999.32
	BIC	15110.90

Reference class for attribute 1 (Equity offered) is: 85%
Reference class for attribute 2 (Premoney) is: 2.000.000€
Reference class for attribute 3 (Professional investors) is: 5 professional investors
Reference class for attribute 4 (Retail investors) is: 355 retail investors
Reference class for attribute 5 (Bids confirmed) is: 100%
Reference class for attribute 6 (Social media) is: Facebook, Instagram, Twitter (X) and LinkedIn
* p<0.10, ** p<0.05, *** p<0.010

Table 8: attribute importance – stepwise backward elimination models

		(1) Full model Coef./(Std. err.)	(2) Reduced model 1 Coef./(Std. err.)	(3) Reduced model 2 Coef./(Std. err.)	(4) Reduced model 3 Coef./(Std. err.)	(5) Reduced model 4 Coef./(Std. err.)	(6) Reduced model 5 Coef./(Std. err.)	(7) Reduced model 6 Coef./(Std. err.)
	Y=choice							
	Status-quo	-0.620***	-0.579***	-0.648***	-0.530***	-0.573***	-0.623***	-0.408***
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
% EQUITY-OFFERED	2% offered	-0.266***		-0.306***	-0.288***	-0.316***	-0.370***	-0.308***
		(0.06)		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
	9% offered	-0.002		-0.037	-0.024	-0.071	-0.107**	-0.049
		(0.05)		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$PRE-MONEY	1.000€ premoney	-0.100*	-0.135**		-0.151***	-0.089	-0.159***	-0.117**
		(0.06)	(0.05)		(0.06)	(0.06)	(0.05)	(0.05)
	10.000€ premoney	0.057	0.046		-0.018	0.028	-0.027	0.043
		(0.06)	(0.06)		(0.05)	(0.06)	(0.05)	(0.05)
N-PROF-INVESTORS	0 professional investors	-0.307***	-0.316***	-0.294***		-0.323***	-0.334***	-0.231***
		(0.05)	(0.05)	(0.05)		(0.05)	(0.05)	(0.05)
	1 professional investors	-0.143***	-0.155***	-0.144***		-0.174***	-0.169***	-0.080*
		(0.05)	(0.05)	(0.05)		(0.05)	(0.05)	(0.05)
N-RET-INVESTORS	16 retail investors	-0.275***	-0.282***	-0.250***	-0.297***		-0.312***	-0.239***
		(0.05)	(0.05)	(0.05)	(0.05)		(0.05)	(0.05)
	122 retail investors	-0.057	-0.073	-0.049	-0.080		-0.144***	-0.065
		(0.06)	(0.05)	(0.06)	(0.05)		(0.06)	(0.05)
%INVEST-CONFIRM	0% confirmed	-0.713***	-0.746***	-0.726***	-0.745***	-0.719***		-0.754***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)		(0.05)
	88% confirmed	-0.049	-0.093*	-0.075	-0.096*	-0.063		-0.069
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)		(0.05)
SOCIALS	None	-0.384***	-0.380***	-0.392***	-0.332***	-0.338***	-0.476***	
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	
	Twitter (X) and/or LinkedIn	-0.239***	-0.244***	-0.262***	-0.187***	-0.265***	-0.257***	
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	
	Facebook and/or Instagram	-0.156**	-0.121**	-0.186***	-0.149**	-0.145**	-0.198***	
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	
	N	1018	1018	1018	1018	1018	1018	1018
	Pseudo R-squared	0.04	0.04	0.04	0.04	0.04	0.02	0.04
	AIC	14999.32	15041.89	15009.59	15031.27	15035.57	15331.14	15048.89
	BIC	15110.90	15137.53	15105.23	15126.92	15131.21	15426.78	15136.57

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

Regarding the new venture's social media accounts, retail investors tend to interpret the absence of social media as a strong and significant negative signal (average b=-0.384 and s.e.=0.05), but they also tend to prefer as large a social media presence as possible (four active profiles: Facebook, Instagram, Twitter (X), and LinkedIn).

We also controlled for the status quo, which is the no-choice alternative, reporting a significant negative coefficient of -0.620 ($p < 0.001$) and suggesting a significant propensity to choose one of the investment alternatives in each choice set.

A series of stepwise backward regressions is then employed to understand the relative importance of each attribute. The loss of information caused by the sequential elimination of one attribute at a time provides insights about the relative attribute importance. The estimation results from the six additional reduced models, as well as the models' fit statistics and information criteria, are reported in Table 8.

Likelihood-ratio (LR) tests are employed to compare the goodness of fit of nested models and to test for statistical differences between the full model and the reduced models. The LR tests, along with the comparison of information criteria (such as Akaike's Information Criterion, AIC), allow us to reconstruct the attribute ranking as perceived by retail investors. Results are synthetized in Table 9.

Table 9: attribute importance – baseline model

	Attribute	LR test	AIC
1	Financial commitment	335.82***	15331.14
2	Social media	55.57***	15048.89
3	Equity offered	46.57***	15041.89
4	Retail investors	40.25***	15035.57
5	Professional investors	35.96***	15031.27
6	Pre-money	14.27***	15009.59

AIC full model = 14999.32

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

The financial commitment attribute exhibits the highest LR test statistic at 335.82 ($p < 0.01$), indicating a substantial impact on the model's explanatory power. This is supported by a larger AIC score of 15331.14 if compared to the reference point of the full model (AIC of 14999.32). The second attribute in importance is Social Media, which is statistically distant (LR of 55.57 and AIC of 15048.89) from the first attribute. The last attribute in importance is pre-money, with a LR of 14.27 and AIC closer to the reference model (15009.59).

6.2.The moderation of FK

Our baseline specification analyzes the impact of various sources of information on the investment propensity of retail investors. In other words, it estimates which information sources individuals consider when selecting ECF campaigns to invest in, among those provided by the platforms. However, it is interesting to examine the role of financial knowledge in their decision-making process and whether it plays a moderating role. For instance, retail investors with high levels of financial knowledge (FK) may consult sources that possess private information or imitate the behavior of more informed economic agents. **Error! Not a valid bookmark self-reference.** reports the estimation results of the sub-groups per levels of FK, providing insights into the moderating role of the variable.

The results indicate that retail investors with higher levels of FK have no significant preference toward pre-money valuation compared to individuals with lower levels of FK.

Table 10: sub-group regression models per levels of financial knowledge

		(1) Low FK Coef./(Std. err.)	(2) High FK Coef./(Std. err.)
	Y=choice		
	Status-quo	-0.172	-1.043***
		(0.12)	(0.12)
% EQUITY-OFFERED	2% offered	-0.169**	-0.374***
		(0.08)	(0.08)
	9% offered	-0.003	-0.003
		(0.08)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.168**	-0.038
		(0.08)	(0.08)
	10.000€ premoney	-0.007	0.125
		(0.08)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.082	-0.516***
		(0.08)	(0.07)
	1 professional investors	0.019	-0.291***
		(0.07)	(0.07)
N-RET-INVESTORS	16 retail investors	-0.166**	-0.390***
		(0.08)	(0.08)
	122 retail investors	-0.019	-0.091
		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.525***	-0.888***
		(0.07)	(0.07)
	88% confirmed	-0.090	0.000
		(0.07)	(0.07)
SOCIALS	None	-0.228***	-0.549***
		(0.08)	(0.08)
	Twitter (X) and/or LinkedIn	-0.198**	-0.274***
		(0.08)	(0.08)
	Facebook and/or Instagram	-0.148*	-0.159*
		(0.09)	(0.09)
	N	492	526
	Pseudo R-squared	0.04	0.07
	AIC	7331.59	7565.10
	BIC	7432.99	7667.43

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

In contrast, individuals with higher levels of FK show a significantly strong preference for investment alternatives in which more professional investors with private information have already invested. Therefore, moderating role of FK let us assume that crowd-investors with high FK understand the importance and utility of private information.

Table 11 reports the results of the nested (reduced) model estimates to capture the importance of each attribute in the case of high financial knowledge.

The results of attribute importance in the investment decision-making process of retail investors with high FK, as measured by LR tests and AIC scores are then synthesized in Table 12.

The financial commitment attribute stands out with a substantial LR test statistic of 289.60, indicating a strong impact on the model's explanatory power. This is supported by an AIC score of 7850.699, underscoring the attribute's significance in influencing their investment choices.

Table 11 attribute importance – high financial knowledge - stepwise backward elimination models

		(1) High FK Coef./(Std. err.)	(2) Reduced model 1 Coef./(Std. err.)	(3) Reduced model 2 Coef./(Std. err.)	(4) Reduced model 3 Coef./(Std. err.)	(5) Reduced model 4 Coef./(Std. err.)	(6) Reduced model 5 Coef./(Std. err.)	(7) Reduced model 6 Coef./(Std. err.)
	Y=choice							
	Status-quo	-1.043***	-0.981***	-1.115***	-0.864***	-0.978***	-1.106***	-0.802***
		(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)
% EQUITY-OFFERED	2% offered	-0.374***		-0.400***	-0.407***	-0.442***	-0.486***	-0.430***
		(0.08)		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
	9% offered	-0.003		-0.028	-0.040	-0.110	-0.133*	-0.072
		(0.08)		(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.038	-0.096		-0.123	-0.034	-0.110	-0.074
		(0.08)	(0.08)		(0.08)	(0.08)	(0.08)	(0.08)
	10.000€ premoney	0.125	0.093		0.002	0.074	-0.004	0.085
		(0.08)	(0.08)		(0.08)	(0.08)	(0.07)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.516***	-0.523***	-0.490***		-0.531***	-0.539***	-0.406***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.07)
	1 professional investors	-0.291***	-0.304***	-0.289***		-0.328***	-0.312***	-0.209***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.06)
N-RET-INVESTORS	16 retail investors	-0.390***	-0.381***	-0.363***	-0.428***		-0.459***	-0.324***
		(0.08)	(0.07)	(0.08)	(0.08)		(0.08)	(0.08)
	122 retail investors	-0.091	-0.103	-0.085	-0.133*		-0.248***	-0.117
		(0.08)	(0.08)	(0.08)	(0.08)		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.888***	-0.932***	-0.903***	-0.942***	-0.900***		-0.950***
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
	88% confirmed	0.000	-0.061	-0.040	-0.079	-0.027		-0.056
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
SOCIALS	None	-0.549***	-0.538***	-0.558***	-0.448***	-0.476***	-0.632***	
		(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	
	Twitter (X) and/or LinkedIn	-0.274***	-0.287***	-0.301***	-0.178**	-0.302***	-0.311***	
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	
	Facebook and/or Instagram	-0.159*	-0.118	-0.201**	-0.131	-0.149*	-0.232***	
		(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	
	N	526	526	526	526	526	526	526
	Pseudo R-squared	0.07	0.06	0.07	0.06	0.06	0.04	0.06
	AIC	7565.10	7608.66	7569.38	7613.19	7601.29	7850.70	7620.88
	BIC	7667.43	7696.37	7657.10	7700.91	7689.01	7938.42	7701.29

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

Table 12 attribute importance – high financial knowledge

High FK

	Attribute	LR test	AIC
1	Financial commitment	289.60***	**7850.699**
2	Social media	61.78***	**7620.88**
3	Professional investors	52.10***	**7613.192**
4	Equity retention	47.56***	**7608.657**
5	Retail investors	40.20***	**7601.292**
6	Pre-money	8.28**	**7569.378**

AIC full model = 7565.095

Additionally, this attribute shows four times the magnitude of the second emerging feature, which is social media presence (LR test statistic of 61.78 and AIC of 7620.88). However, it is noteworthy that individuals with high levels of FK value information from professional investors more, which ranks third in the attribute importance.

6.3.The moderation of DA

Table 13 sub-group regression models per levels of digital agency

		(1) Low DA Coef./(Std. err.)	(2) High DA Coef./(Std. err.)
	Y=choice		
	Status quo	-0.208*	-1.038***
		(0.12)	(0.12)
% EQUITY-OFFERED	2% offered	-0.241***	-0.321***
		(0.08)	(0.08)
	9% offered	0.022	-0.034
		(0.08)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.081	-0.137*
		(0.08)	(0.08)
	10.000€ premoney	-0.025	0.117
		(0.08)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.172**	-0.429***
		(0.08)	(0.07)
	1 professional investors	-0.011	-0.253***
		(0.07)	(0.07)
N-RET-INVESTORS	16 retail investors	-0.200**	-0.353***
		(0.08)	(0.08)
	122 retail investors	0.012	-0.124
		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.475***	-0.936***
		(0.07)	(0.07)
	88% confirmed	-0.036	-0.059
		(0.07)	(0.07)
SOCIALS	None	-0.377***	-0.397***
		(0.08)	(0.08)
	Twitter (X) and/or LinkedIn	-0.326***	-0.144*
		(0.08)	(0.08)
	Facebook and/or Instagram	-0.229***	-0.084
		(0.09)	(0.09)
	N	498	520
	Pseudo R-squared	0.05	0.07
	AIC	7356.54	7510.74
	BIC	7458.11	7612.92

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

Table 14 attribute importance – high digital agency - stepwise backward elimination models

		(1) High DA Coef./(Std. err.)	(2) Reduced model 1 Coef./(Std. err.)	(3) Reduced model 2 Coef./(Std. err.)	(4) Reduced model 3 Coef./(Std. err.)	(5) Reduced model 4 Coef./(Std. err.)	(6) Reduced model 5 Coef./(Std. err.)	(7) Reduced model 6 Coef./(Std. err.)
	Y=choice							
	Status quo	-1.038***	-0.979***	-1.108***	-0.881***	-0.965***	-1.059***	-0.890***
		(0.12)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)
% EQUITY-OFFERED	2% offered	-0.321***		-0.378***	-0.345***	-0.389***	-0.423***	-0.355***
		(0.08)		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
	9% offered	-0.034		-0.088	-0.061	-0.132*	-0.157**	-0.073
		(0.08)		(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.137*	-0.187**		-0.212***	-0.127	-0.182**	-0.161**
		(0.08)	(0.08)		(0.08)	(0.08)	(0.08)	(0.08)
	10.000€ premoney	0.117	0.092		0.015	0.084	0.008	0.085
		(0.08)	(0.08)		(0.08)	(0.08)	(0.07)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.429***	-0.436***	-0.405***		-0.446***	-0.464***	-0.361***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.07)
	1 professional investors	-0.253***	-0.260***	-0.259***		-0.291***	-0.278***	-0.208***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.06)
N-RET-INVESTORS	16 retail investors	-0.353***	-0.358***	-0.313***	-0.386***		-0.432***	-0.292***
		(0.08)	(0.07)	(0.08)	(0.08)		(0.08)	(0.08)
	122 retail investors	-0.124	-0.140*	-0.110	-0.155**		-0.283***	-0.139*
		(0.08)	(0.08)	(0.08)	(0.08)		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.936***	-0.971***	-0.952***	-0.984***	-0.951***		-0.993***
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
	88% confirmed	-0.059	-0.110	-0.106	-0.127*	-0.080		-0.111
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
SOCIALS	None	-0.397***	-0.397***	-0.415***	-0.315***	-0.337***	-0.500***	
		(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	
	Twitter (X) and/or LinkedIn	-0.144*	-0.163**	-0.189**	-0.060	-0.167**	-0.199***	
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	
	Facebook and/or Instagram	-0.084	-0.051	-0.144*	-0.053	-0.076	-0.149*	
		(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	
	N	520	520	520	520	520	520	520
	Pseudo R-squared	0.07	0.06	0.06	0.06	0.06	0.03	0.06
	AIC	7510.74	7537.19	7526.42	7543.26	7535.43	7808.65	7540.98
	BIC	7612.92	7624.77	7614.00	7630.84	7623.01	7896.23	7621.27

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

Similarly, it is interesting to consider the role of digital agency in retail investors' decision making and analyze its moderating role. For example, retail investors with high levels of digital agency (DA) are believed to be more likely to use digital finance tools and more confident in seeking relevant financial information or gaining knowledge through the experience or behaviour of better-informed agents. Table 13 reports the estimation results of the sub-groups per levels of FK, providing insights into the moderating role of the variable.

The results suggest that retail investors with higher levels of DA value information coming also from fewer social media compared to individuals with lower levels of DA. In particular, the latter value more the number (4) of social media accounts, whether the former value also the substance of the different social media. They are wary of investment campaigns without social media, but feel it is sufficient to guide their investment decision to have at least two social media accounts and, in particular, Facebook and/or Instagram. Twitter (X) and/or LinkedIn alone seem to be disliked when compared with the presence of four social media, but with partial statistical significance. At the same time, individuals with higher levels of DA show a significantly strong preference for investment alternatives in which multiple professional investors with private information have already invested, whether individuals with low levels of DA consider the presence of at least one professional investor to be sufficient.

Table 14 reports the results of the nested (reduced) model estimates to capture the importance of each attribute in the case of high DA. The results of attribute importance in the investment decision-making process of retail investors with high DA, as measured by LR tests and AIC scores are then synthesized in Table 15.

Financial commitment emerges once again as the most influential attribute, as evidenced by the highest LR test statistic of 301.91, which is more than eight times larger than the second attribute, and an associated AIC of 7808.65. However, the results also show that information from professional investors becomes even more important to retail investors with high DA. On the other hand, information from social media loses one position and ranks third for individuals with higher levels of digital competence, confidence and accountability.

Table 15 attribute importance – high digital agency

High DA			
	Attribute	**LR test**	**AIC**
1	Financial commitment	301.91***	7808.65
2	Professional investors	36.52***	7543.26
3	Social media	36.24***	7540.98
4	Equity retention	30.45***	7537.19
5	Retail investors	28.69***	7535.43
6	Pre-money	19.68***	7526.42
		AIC full model = 7510.74	

7. Discussion

Given the transactional complexities associated with information acquisition, including its interpretation and dissemination, ECF platforms play a key role in ameliorating these challenges. Designed to facilitate the provision, exchange, and interpretation of information, they enable potential investors to discern the most suitable investment opportunities within early-stage innovative companies.

In fact, information is often considered a valuable resource that enhances decision-making processes across various domains, including finance (Macauley, 2006). In the context of the financial markets, the economic value of information lies in its ability to reduce uncertainty and provide insights into future events. Investors seek information to gain a competitive edge, mitigate risks, and capitalize on emerging opportunities. The value of information is contingent on its relevance, accuracy, and timeliness (Rascão, 2021).

Indeed, the preferences of retail investors, generally not skilled and trained in finance, are shaped by the information available to them, and understanding their behavior is essential for developing a nuanced comprehension of market dynamics, especially in an innovative environment such as the ECF.

Administering a Discrete Choice Experiment to a sample of N=1,018 Italian household heads, representative of Italian consumers and retail investors, their preferences are analyzed across different types of information (public vs private, hard vs soft) affecting their decision-making, allegedly guiding their herding behavior. As expected, the findings show that these individuals are influenced more significantly by public information sources (the percentage of equity already paid by other investors and the number of social media networks managed by the startup) and less by private ones (the number of professional investors and the pre-money evaluation of the startup).

In particular, the financial commitment of the investor crowd appears to be the most influential source of information overall, with an impact on investor choice ranging from 4 to 8 times the magnitude of other sources of information. It represents public information and is soft in nature. Similarly, our results indicate that the second most influential attribute is again a public source of information, namely the number of social media accounts associated with the new venture. Conversely, the last two sources of information for magnitude are the number of professional investors and the pre-money valuation that both encompass private information. Therefore, Hypothesis 1a is supported by the evidence from our sample, and one can imagine that retail crowd-investors consult and understand public rather than private information better; conversely, results offer mixed evidence for H1b because the first source is a soft one (investors' commitment) and the second source is a hard one (the number of social media organized by the startup).

Additionally, this study uncovers a moderation role of financial knowledge and digital agency. In fact, individuals with higher levels of financial knowledge upscale the perceived importance of the presence of financial professionals (soft, private information). Therefore, our data partially supports evidence for Hypothesis 2.

The aforementioned upscale is even higher for individuals who exhibit high levels of digital agency, which again offers partial support for Hypothesis 3. Indeed, retail investors with higher degrees of digital competence, trust, and responsibility tend to value information from professional investors (private and soft) significantly more. The results also allow us to infer that individuals with greater familiarity with digital technologies tend to value dynamic and fluid information, i.e., soft information, more highly.

8. Conclusive remarks

In conclusion, the findings of this study shed light on the intricate dynamics governing the decision-making processes of non-professional, non-skilled investors in the realm of ECF. The observed herding behavior among ECF investors, driven by a perceived need to compensate for gaps in knowledge, skills, and experience, underscores the critical role of information in guiding investment choices. Notably, the DCE administered in the period of December 2022 - January 2023 to a representative sample of Italian household heads revealed a distinct preference for public information sources, particularly the percentage of equity already paid by other investors and the number of social networks managed by the startup. This inclination towards publicly available data suggests a reliance on collective wisdom and social signals in the decision-making process. Contrarily, private information sources, such as the involvement of professional investors and the pre-money evaluation of the startup, exerted a comparatively lesser influence on investor choices. This effect, however, is subject to the moderation of financial knowledge and digital agency.

Indeed, individuals with higher levels of financial literacy displayed an augmented emphasis on the presence of financial professionals in guiding their investment decisions. This effect was even more pronounced among individuals exhibiting high levels of digital agency, underlining the increasing importance of technological proficiency in shaping investor preferences. This nuanced interplay between financial literacy, digital agency, and information preferences highlights the need for targeted educational programs aimed at enhancing both financial literacy and digital competencies within a given population.

As countries strive to foster vibrant entrepreneurial ecosystems, our findings advocate for comprehensive educational initiatives that not only bolster financial literacy but also cultivate digital agency among the populace. Policymakers, institutions, and private entities should collaborate in designing and implementing programs aimed at elevating the sophistication of investors, thereby fostering a more informed and resilient investment landscape within the rapidly evolving domain of equity crowdfunding.

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