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# Are Digital Finance Markets Inclusive? Evidence From Equity Crowdfunding Investors

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## ABSTRACT

Digital finance promises to reduce barriers in financial markets, yet its inclusiveness remains uncertain. This paper examines individual investors in equity crowdfunding (ECF) using data from 20,209 registered users on Italy's largest ECF platform. We analyze gender, age, location and ethnicity in investment decisions. Our findings challenge traditional finance views: women and ethnic minorities invest more and in larger amounts, while younger individuals invest less, contradicting assumptions about digital finance appealing to youth. No significant differences emerge between rural and metropolitan investors, suggesting that digital access alone does not eliminate geographic barriers.

**JEL Classification:** G30

## 1 | Introduction

Within the rapidly evolving entrepreneurial finance industry, digitalization introduced a technological change, making it possible for individual investors to directly invest their own money in early-stage investments. Regulators and policy-makers agree that the disintermediation brought about by entrepreneurial finance brought by digitalization brings new challenges, together with unprecedented opportunities (e.g., Greenspan 2005, Dodd-Frank 2013). This paper investigates whether digital finance fulfills its potential to democratize entrepreneurial finance by enabling underrepresented groups—such as women, younger individuals, ethnic minorities, and rural residents—to actively participate as investors.

Despite extensive efforts worldwide to promote financial market participation, significant disparities persist across demographic and geographic groups. According to the Federal Reserve's 2022 survey, 58% of families own stocks. However, ownership is uneven, with 34% of lower-income families owning stocks compared to 78% in the upper–middle-income group and 95% in the top decile (Federal Reserve Board 2023). Women are less likely to invest in stock markets than men (Bogan 2008; Lusardi and Mitchell 2007). Ethnic disparities are also pronounced, with White households holding significantly more financial assets than Black and Hispanic households (Chakrabarti et al. 2024). Age disparities further underscore these inequities, as 62% of adults aged 30–64 own stocks compared to just 31% of those aged 18–29 (Gallup 2017). Additionally, rural residents face structural barriers such as limited access to financial institutions and investment networks (Brown et al. 2008).

Research highlights a variety of factors contributing to these persistent disparities. Economic barriers, including transaction costs, income and liquidity needs (Allen and Gale 1994), minimum investment thresholds (Haliassos and Bertaut 1995), and financial literacy (Campbell 2006) create significant barriers to market entry. Behavioural explanations, such as ambiguity aversion and personal preferences (Haliassos and Bertaut 1995) offer further insights into why women, younger individuals, and ethnic minorities may exhibit heightened reluctance to invest. In addition, geographical and social isolation limit opportunities for rural residents, while exclusion from established financial networks perpetuates inequities for underrepresented groups.

Entrepreneurial finance equity markets reflect similar patterns of exclusion. Private equity and venture capital deals are predominantly negotiated among a select group of professional investors, often characterized as older, white males based in major financial hubs (Chen et al. 2010). In the period 1990–2016, women have been less than 10% of the venture capital-labour pool–with only 15% of gender-balanced senior investment teams (International Finance Corporation, Oliver Wyman, RockCreek 2019)–, Hispanic people have been around 2%, and African American people have been less than 1%. This exclusivity stems from relational barriers, high capital requirements, and the inherent risks associated with these markets. Consequently, opportunities for participation by other demographic groups have historically been limited.

Digital finance, specifically equity crowdfunding (ECF), offers a promising alternative to access to entrepreneurial finance. Unlike private equity or venture capital, crowdfunding platforms publicly share information about investment opportunities and lower barriers to entry (Cumming et al. 2021b; Kazembalaghi et al. 2025). While these platforms expose investors to fraud risk, they also reduce transaction costs and capital requirements, broadening investor participation (Butticè and Vismara 2022). For women, crowdfunding provides a more inclusive and accessible path to financial engagement. Rural residents benefit from the online nature of these platforms, which mitigates geographical constraints. Similarly, younger individuals and ethnic minorities, often excluded from traditional financial markets, may find crowdfunding an accessible entry point into entrepreneurial finance.

The aim of our research is to investigate how age, gender, geographical location, and ethnicity shape investors' behaviour within the context of ECF. Specifically, we analyze how these dimensions influence the likelihood of becoming an active investor and the amount invested, among individuals who have registered on a crowdfunding platform. Although these dimensions have been widely identified as sources of disadvantage in traditional entrepreneurial finance markets, where women, ethnic minorities, younger individuals, and rural residents tend to be underrepresented among investors, the dynamics may differ in the context of ECF. This is because ECF lowers structural barriers to entry and offer broader, more decentralized access to investment opportunities. In other words, for some underrepresented groups, ECF may represent the only accessible channel to participate in entrepreneurial finance, thus encouraging them to more fully exploit the opportunities available within this environment. In addition, ECF platforms feature demand-side characteristics, such as a higher presence of women-led ventures, tech-driven campaigns, or socially oriented initiatives compared to traditional markets, that may further engage individuals typically excluded from traditional finance.

To address our research question, we use data from 20,209 registered individuals on the largest ECF platform in Italy for the period May 2016–December 2023. This study examines how demographic and geographic factors shape participation in ECF. Our analysis is based on proprietary data provided by the ECF platform, enabling us, for the first time, to perform a fine-grained analysis of otherwise unobservable characteristics of individual investors. Specifically, we examine how age, gender, geographical location, and ethnicity influence the likelihood of becoming active investors and the amounts invested. However, the analysis is conditional on the prior decision to register on the ECF platform, which is nonrandom.

To address this, we employ a two-stage selection model with instrumental variables estimated through Bayesian analysis via Markov Chain Monte Carlo (MCMC) estimation via random-walk Metropolis-Hastings sampling (Hastings 1970). Bayesian estimates mitigate endogeneity concerns by incorporating prior information and explicitly modeling uncertainty, leading to a more cautious approach to inferences (Sørensen 2007). This framework explicitly models sample selection and introduces priors that improve inference when the sample is nonrepresentative and when certain subgroups are underrepresented. Specifically, in our main model, we use demographic information from external populations to inform the prior distributions in our Bayesian estimation using demographics from traditional investors in entrepreneurial finance, specifically venture capitalists (VCs) and business angels (BAs). VCs and BAs represent a highly selective group of professional investors, offering insight into the demographic composition of those historically active in entrepreneurial finance—although they exclude individuals without access to traditional networks or capital, precisely those whom digital finance seeks to include. While neither group serves as a direct comparison sample, incorporating both sets of priors allows us to condition our estimates on contrasting reference points, thereby enriching our understanding of the demographic structure of ECF participants. Additionally, we conduct robustness tests on prior sensitivity, and we apply traditional econometric techniques of estimation to compare the magnitude of the effects and support the reliability of our findings.

The findings reveal significant heterogeneity in participation patterns, suggesting that equity crowdfunding can broaden access to investment opportunities and reduce disparities in financial market participation. Specifically, we find that female investors are more likely to participate and invest a higher amount of capital than their male counterparts. Similarly, ethnic minority individuals show a higher probability of participating and investing more than nonminority investors. Interestingly, younger investors were less likely to participate and invested a lower amount of capital than older investors, challenging the notion that crowdfunding automatically appeals to younger demographics. Rural residents do not have a higher likelihood to invest than metropolitan residents; however, investors from metropolitan areas tend to invest larger amounts compared to their rural counterparts.

The remainder of the paper is structured as follows: Section 2 reviews prior literature and develops the hypotheses. Section 3 describes the research design and methodology. Section 4 presents the empirical results, and Section 5 concludes.

## 2 | Institutional Background: The Investment Process in Equity Crowdfunding

Traditionally, entrepreneurs raising external equity face two types of opportunities, namely private and public equity. In private equity, the deal is between the entrepreneur and a restricted number of providers of capital. The latter can either directly invest their own money, such as in the case of business angels, or act through intermediation. This is the case with venture capitalists and other types of private equity funds, where investment decisions are made by general partners (money managers) on behalf of other limited partners. In any case, in private equity deals, entrepreneurs can choose who they deal with and are able to negotiate the terms of the contract, including the price and the number of shares. When valuing to take an equity position in startups, venture capitalists and business angels rely heavily on due diligence predicated on face-to-face interactions and personal relationships. Such private deals typically are "pitched" in person to investors who engage in significant due diligence, and may seek an ongoing management role within the company to protect their investment.

As an alternative, entrepreneurs can raise external equity by listing on a stock exchange. The capital inflow takes place by means of an open offering. In initial public offerings (IPOs), the ownership base of firms going public is open to the general public (e.g., Ritter 1987). Issuers broadly solicit and advertise their securities to investors, without the possibility to discern and select who is going to receive the shares of their company. Investment banks serving as IPO underwriters are in charge of the pricing and allocation of shares (Migliorati and Vismara 2014). Once the offering is listed on the stock exchange, the price is fixed and the ownership structure is solely defined by investors' demand for shares. A primary role in these offerings, therefore, is covered by investment banks, whose function is to match and balance the objective of the demand and supply of capital.

Equity crowdfunding is distinct from both IPOs and venture capital and business angel investments, as it occupies a middle space between public and private finance (e.g., Vismara 2022). Similar to traditional private deals, equity crowdfunding provides issuers with a method for obtaining equity financing without bearing the full costs of registering the securities with the national securities and exchange commissions. Occasionally, ECF and private deals can complement each other, as successful crowdfunding campaigns may attract private investors seeking validated early-stage opportunities and who can monitor the issuer after the deal (Coakley et al. 2022). However, while traditional private deals are limited to a relatively small group of private investors, equity crowdfunding allows issuers to involve small investors (Coakley et al. 2025). This diversity is reflected in the variety of businesses seeking crowdfunding finance. Venture capitalists typically invest in companies with scalable business models in high-growth industries and located in specific geographic locations. This focus limits their appeal to entrepreneurs in human capital-intensive industries or any way with business models lacking the ability to easily scale. On the contrary, equity crowdfunding offerings are mostly in traditional sectors (Butticè et al. 2020).

Equity crowdfunding platforms list offerings open to the public, similar to traditional stock exchanges (Vismara 2022). However, unlike traditional public offerings, which are subject to a host of regulations designed to protect the interests of investors, equity crowdfunding is available to a wide variety of early-stage firms and is substantially less costly for issuers (e.g., Butticè and Vismara 2022). Thus, it comes as no surprise that many issuers pursue multiple ECF rounds (e.g., Signori and Vismara 2018; Coakley et al. 2022). Relatedly, one significant downside of equity crowdfunding is the lack of liquidity in secondary markets (Johan and Zhang 2020). While crowdfunding provides small investors with a disintermediated 'entry' into venture financing, the prospects for exiting a successful venture are less clear.

Equity crowdfunding markets synthesize the transition from offline to online entrepreneurial finance. Because of the online nature of platform-mediated interactions, it is very unlikely that crowdfunding investors will personally meet the issuers from whom they purchase securities, which differs quite considerably from the hands-on approach typically taken by venture capitalists and angel investors. Crowdfunding platforms allow anyone to view projects posted online, allowing for a more heterogeneous population of backers, which includes small investors (Meoli and Vismara 2021). 'For the first time,' proclaimed President Obama when he signed the JOBS Act, 'ordinary Americans will be able to go online and invest in entrepreneurs that they believe in.'[1]

## 3 | Hypotheses

Multiple studies in the recent literature have investigated whether crowdfunding democratizes access to finance. These investigations have primarily focused on entrepreneurs traditionally marginalized by financial institutions, concentrating on specific individual characteristics such as gender, geographical location, or age (e.g., Gafni et al. 2021; Younkin and Kuppuswamy 2018), or studying multiple characteristics jointly (Cumming et al. 2021a). Comparatively little attention has been paid to the investor side of the market. As a result, it remains unclear whether crowdfunding also facilitates access to financial markets for investors typically excluded from traditional financial channels. This paper posits that crowdfunding holds significant potential to democratize access to finance for these investors, fostering greater inclusivity. Specifically, we focus on groups historically underrepresented in traditional entrepreneurial finance, such as women, ethnic minorities, younger individuals, and rural residents, and assess whether the disadvantages they face in conventional investment channels persist within the ECF context. Our theorizing is internal to the crowdfunding setting as we examine whether disparities in participation and engagement emerge within the population of individuals who have already accessed an ECF platform.

In the following sections, we review the entrepreneurial finance literature across these dimensions. We describe the factors contributing to the underrepresentation in traditional financial markets of these individuals and propose several explanations for why these same individuals may be overrepresented on ECF platforms. We suggest that lower entry barriers compared to traditional finance markets, homophilic matching, and informational advantages may lead to a higher propensity for these investors to participate in ECF. This indicates a democratizing role of this funding source, particularly in terms of investor diversity.

### 3.1 | Gender

A large body of research indicates significant gender disparities in participation in traditional entrepreneurial finance markets. For example, venture capital (VC) markets are predominantly populated by male investors. Approximately 80% of VC partners are male, and this share increases above 90% among partners with at least one board seat (Lerner and Nanda 2020), and in European VC firms (Butticè et al. 2022). Female-led VC funds manage less than 4% of total assets under management (PitchBook-All Raise All 2019). Furthermore, about 75% of VC firms have never had a senior investment professional who is a woman (Gompers et al. 2020), and only 15% of senior investment teams are gender-balanced (International Finance Corporation, Oliver Wyman, RockCreek 2019). This trend will likely persist also in the coming years, considering that women represented less than 10% of new hires in the VC industry from 1990 to 2016 (Calder-Wang and Gompers 2021). The finance literature has explored several reasons for this imbalance, pointing to women's lower risk tolerance (Grable 2000), lower financial literacy (Lusardi and Mitchell 2007), and reduced financial confidence (Barber and Odean 2001) compared to men. This gender disparity in the investor base has significant consequences also for female entrepreneurs seeking funding from traditional entrepreneurial finance channels. Women-led ventures often receive a smaller share of capital than male-led ventures, and the composition of the investor base in traditional entrepreneurial finance markets has been identified as a key factor contributing to this persistent gender gap.

In contrast, evidence from crowdfunding research suggests a more equitable entrepreneurship landscape. Female-led ventures are more likely to succeed in both reward-based and equity-based crowdfunding contexts (e.g., Gafni et al. 2021; Cumming et al. 2021a). Previous scholars often link this success to the presence of female investors in the crowdfunding market, suggesting that crowdfunding attracts more female investors compared to traditional financial markets (Rossi et al. 2021). However, this reason is frequently left implicit in the literature.

In this paper, we embrace this view for two main reasons. The first relates to access to the ECF market compared to traditional markets, while the second concerns the possibility that women may be inherently more likely to engage in ECF than men, due to the specific characteristics of the campaigns promoted on these platforms. Unlike traditional markets, in ECF, anyone can participate and invest by providing basic information and registering on a digital finance platform. Accordingly, virtually anybody is allowed to access the funding means with very limited access costs. These lower entry barriers are likely to affect the composition of the investor base. Indeed, while crowdfunding represents one of the multiple equity capital markets for male investors, it can represent a unique available option for most female investors. Crucially, this limited access to alternative channels does not merely affect whether women enter ECF, but also how they engage with it. While male investors typically have multiple investment avenues available to them and can diversify or allocate resources selectively, women who view ECF as their sole accessible option may be more inclined to fully exploit this opportunity. In this context, the absence of alternatives increases not only the probability that women enter the ECF space but also the likelihood that they invest once there, and potentially with greater amounts. This mechanism suggests that participation in ECF for women may be more likely to lead to investments.

Second, the characteristics of the demand side of ECF markets, which often feature numerous campaigns led by female entrepreneurs, can motivate different investment patterns (Cumming et al. 2021a). Indeed, female investors may find the campaigns launched by female entrepreneurs more aligned with their interests). Again, this supports the idea that female investors have a higher likelihood of investing in crowdfunding and committing a larger amount of financing resources compared to their male counterparts. Overall, the arguments described above suggest higher activism of female investors in ECF markets. Accordingly, this study suggests that female investors are more likely to invest in ECF campaigns compared to male investors and that the amount of capital they invest is higher. Hence, we derive the following hypotheses:

**Hypothesis 1a.** *In equity crowdfunding offerings, female individuals are more likely to become investors than male individuals.*

**Hypothesis 1b.** *In equity crowdfunding, female investors invest a larger amount of capital than male investors during their first investment.*

### 3.2 | Age

Similar to gender, a consistent body of research highlights significant age disparities in traditional entrepreneurial finance equity markets, affecting both the entrepreneurs who gain access to financing and the investors who provide it. Younger individuals often face barriers to accessing traditional financial markets due to factors such as limited financial history and perceived inexperience. These barriers can make it difficult for young entrepreneurs to secure funding.

Similarly, young investors have historically faced difficulties in participating in traditional investment opportunities. In traditional markets, older investors dominate due to their accumulated wealth, established networks, and extensive experience (Korniotis and Kumar 2011). However, the emergence of crowdfunding may present an opportunity for younger investors to participate more in entrepreneurial finance for three main reasons. First, similar to the case of female investors discussed above, crowdfunding platforms reduce entry barriers, making it easier for young investors to participate than in traditional channels. Unlike traditional entrepreneurial finance markets, crowdfunding does not require extensive capital or an established financial history to start investing. For many young individuals, it may represent the only accessible channel for early-stage investing, which can result in both higher representation and more active participation within this context.

Second, young investors may have a higher affinity for digital technology, which may further increase their participation in crowdfunding. Their familiarity with online platforms and digital transactions makes them more likely to engage in crowdfunding compared to older investors who may be less tech-prone. This technological propensity provides young investors with a significant advantage in navigating and utilizing crowdfunding platforms effectively, thus motivating a larger number of young investors to use the platform.

Third, many ECF campaigns are centred around innovative and technology-driven ventures. These campaigns tend to be more appealing for younger investors who are typically more attracted by new technological trends and are endowed with the know-how to understand these campaigns. This informational and cognitive proximity may increase both their interest in and understanding of the investment opportunities offered via ECF.

Taken together, these factors suggest that younger investors are not only more likely to become investors in equity crowdfunding, but also potentially more inclined to invest larger amounts of capital. Hence, we hypothesize:

**Hypothesis 2a.** *In equity crowdfunding, young individuals are more likely to become investors than older individuals.*

**Hypothesis 2b.** *In equity crowdfunding, young investors invest a larger amount of capital than older investors during their first investment.*

### 3.3 | Geographical Location

The literature on traditional sources of financing has widely highlighted the geographical dimension of entrepreneurial finance markets. Studies have shown that both the demand and the supply of capital are largely concentrated in metropolitan areas (Chen et al. 2010), where both investors and entrepreneurs cluster and animate a growing entrepreneurial ecosystem. Indeed, rural investors have fewer opportunities to participate in investments in traditional markets due to the concentration of business opportunities in metropolitan areas (Freire-Gibb and Nielsen 2014). Finance literature has shown that investors tend to prefer geographically close investment opportunities (e.g., French and Poterba 1991; Sulaeman 2014) because of lower information asymmetries, better monitoring capabilities, and lower associated costs. Moreover, investors in remote areas are often aware of fewer investment opportunities compared to their metropolitan counterparts because of limited access to information about these opportunities.

We propose that rural investors are more likely to engage in ECF for two main reasons, again related to accessibility and demand-side characteristics. First, equity crowdfunding can reduce the geographic barriers that typically limit rural investors' participation in traditional entrepreneurial finance. Crowdfunding platforms eliminate many of the constraints associated with physical distance, allowing virtually anyone to access investment opportunities regardless of their location. With minimal access costs, crowdfunding platforms make it easier for rural investors to discover, evaluate, and participate in early-stage ventures. This is particularly important given that investors tend to favour geographically proximate investments due to reduced information asymmetries and monitoring costs. This view is supported by empirical evidence that has shown that online platforms can reduce some distance-related economic frictions such as monitoring progress, providing input, and gathering information. In this sense, ECF may represent the only viable channel for rural investors to access entrepreneurial finance, hence fostering both greater presence and engagement on these platforms.

Second, ECF campaigns are not confined to urban centres. Platforms frequently host projects based in rural or peripheral areas (Cumming et al. 2021a), thereby offering rural investors more opportunities to engage with ventures that are geographically proximate. The availability of local campaigns allows rural investors to exercise a home bias, a well-documented tendency in which investors prefer projects located near them (Parwada 2008). While in traditional finance, home bias may reinforce inequality by favouring urban investors exposed to denser opportunity flows, in the context of ECF, it can act as a mechanism of *inclusion* for rural investors. These investors may feel a stronger connection to nearby projects and possess greater local knowledge, which enhances their perceived ability to evaluate and support them (Lin and Viswanathan 2016). As a result, home bias in ECF may increase both the likelihood of rural investors participating and the intensity of their investment once engaged. Hence, we hypothesize:

**Hypothesis 3a.** *In equity crowdfunding, individuals located in rural areas are more likely to become investors than individuals located in metropolitan areas.*

**Hypothesis 3b.** *In equity crowdfunding, investors located in rural areas invest a larger amount of capital than those located in metropolitan areas during their first investment.*

### 3.4 | Ethnicity

Finally, the literature on traditional sources of financing has consistently shown significant disparities based on ethnicity, affecting both entrepreneurs and investors. Ethnic minority investors encounter difficulties in gaining access to investment opportunities in traditional markets due to discriminatory biases (Asiedu et al. 2012). For example, a recent study by the National Venture Capital Association found that only 3% of investment partner positions in VC firms are held by Black employees, Black employees comprise 3% of investment professionals who originate deals, and 3% of the managers who represent the VC firms on the boards of portfolio companies (National Venture Capital Association 2023). Similarly, Hispanic venture capitalists account for only 3.2% of new venture capitalists in the period 2010–2015 (Calder-Wang and Gompers 2021). Additionally, ethnic minority investors may face challenges in accessing new investment opportunities, as these opportunities often arise outside their existing networks, making them either unknown or difficult to evaluate.

Equity crowdfunding provides a promising solution to these challenges. Crowdfunding platforms reduce many of the traditional barriers that ethnic minority investors face, including low social integration within the hosting community and discrimination (Buttiè and Vismara 2022). The small investment size and the close-to-zero access fees also allow investors with lower levels of wealth to gain access to investment opportunities. Similarly, as crowdfunding platforms facilitate access to information about new entrepreneurial projects, it becomes easier for ethnic minority investors to discover and support new ventures. Furthermore, the presence of ethnic-entrepreneurs-led campaigns in ECF platforms can itself motivate greater activism among ethnic investors who may find the investment opportunities more aligned with their interests and possess an information advantage in evaluating these campaigns (Vismara 2018). Finally, crowdfunding reduces geographical barriers and allows investors located outside the country where the entrepreneurial initiative is set to participate in the campaign (Butticè and Useche 2022). Considering that ethnic-led entrepreneurial ventures may be overrepresented in ECF, it is reasonable to expect a disproportionate share of investors who belong to the same ethnic group of entrepreneurs and are from the same country of origin. These investors can have direct relationships with the entrepreneur or can feel a stronger connection and commitment to supporting businesses within their communities, and thus can be willing to invest a larger amount of capital. All in all, this supports the idea that ethnic investors have a higher likelihood of investing in crowdfunding and committing a larger amount of financial resources. Thus:

**Hypothesis 4a.** *In equity crowdfunding, ethnic minority individuals are more likely to become investors than nonminority individuals.*

**Hypothesis 4b.** *In equity crowdfunding, ethnic minority investors invest a larger amount of capital than nonminority investors during their first investment.*

## 4 | Research Design

### 4.1 | Data

The data in our study comprises the population of registered individuals on the largest Italian ECF platform from May 2016 to December 2023. The initial data set is made of 20,329 observations. To focus on individual-level demographics, we exclude 49 observations related to institutional investors, retaining only observations relative to individuals who are registered on the ECF platform for personal investment purposes. We further exclude 50 observations corresponding to individuals who placed an initial investment but withdrew it before confirming the transaction. Therefore, the final data set is made of 20,209 registered individuals on the largest Italian ECF platform from May 2016 to December 2023. Italy serves as a valuable case study for ECF research, having been the first country to introduce comprehensive regulations for this type of entrepreneurial finance market. We access anonymized information about the demographic characteristics of the individuals registered on the ECF platform. This extensive data set, encompassing demographics such as gender, age, location, ethnicity, education, profession, and income, alongside investment decisions (timing and amount), provides a unique opportunity to analyze investor behaviour and the factors influencing their participation in the ECF market.

### 4.2 | Variables

#### 4.2.1 | Dependent Variables

We define two dependent variables for our analysis. First, we consider a dummy variable (*Investor)* equal to 1 if an individual has invested on the platform at least once, thus becoming an investor, and 0 otherwise. Second, we consider the amount of the first investment by each investor on the ECF platform (*Investment amount*).

#### 4.2.2 | Demographic Variables

We consider four individual demographic variables to test our hypotheses. First, we employ a dummy variable (*Female*) which is equal to 1 if the individual registered on the ECF platform is female, and 0 otherwise. Second, we employ a discrete variable *(Age)* that accounts for an individual's age, in years, at the time of registration on the ECF platform. Third, we employ a dummy variable *(Metropolitan area)* which is equal to 1 if the individual registered on the ECF platform resides in a metropolitan area, as defined by the Global Metro Monitor 2020 classification, and 0 otherwise.[2] Finally, we employ a dummy variable (*Ethnic minority*) which is equal to 1 if the individual is identified as an ethnic minority (i.e., nonwhite); 0 otherwise.[3]

#### 4.2.3 | Control Variables

We control for a series of variables related to the individual. We control for the education level of the individual registered on the ECF platform using a dummy variable (*Higher education*), which is equal to 1 if the individual has obtained or is pursuing a bachelor's degree or higher, and 0 otherwise. We control for profession using a dummy variable (*Entrepreneur or manager*), which is equal to 1 if the individual is an entrepreneur or a business manager, and 0 otherwise. We classify individuals according to their annual income, which is reported on the ECF platform in discrete categories: below €10,000; €10,000–€50,000; €50,000–€75,000; €75,000–€100,000; €100,000–€200,000; and above €200,000. To control for the income in our analysis, we assign each observation the mean value corresponding to its income category. We consider potential competition on the platform by measuring for each individual the number of other individuals registered on the platform at the moment of registration (*Competing individuals*). Finally, we control for the Gross Domestic Product (GDP) per capita in the geographical area in which the individual resides, expressed in euros (*GDP per capita*).

#### 4.2.4 | Instrumental Variables

The variables used in our empirical analysis face potential endogeneity concerns, which we address through the implementation of instrumental-variable techniques. Specifically, individual demographic characteristics may be endogenous to the decision to register on the ECF platform. Moreover, these characteristics may also be correlated with investment behaviour by unobserved factors, influencing both the likelihood of investing and the amount invested. For this reason, in our estimations, *Female*, *Age*, *Metropolitan area*, and *Ethnic minority* are instrumented with a variable that measures the percentage of broadband access in households at the regional level (*Broadband access*) using data from Eurostat[4] and matching it to each registered individual's address region, as well as four other variables that identify mimicking behaviour on the ECF platform.[5] Mimicking variables are being used in financial studies on IPOs (e.g., Bell et al. 2012), as well as ECF (e.g., Cumming et al. 2019). Accordingly, we construct a reference measure for each endogenous variable (i.e., *Female, Age, Metropolitan area, Ethnic minority*). For each observation (individual), the measures are calculated as the average of the corresponding variable among all other individuals registered on the platform in the preceding 12 months. The inclusion of these instruments in the specification of the potentially endogenous variables enables a more accurate analysis of mimicking behaviour on the ECF platform and ensures the identification of the full model. We describe the variables employed in our analysis in Table 1.

## 4.3 | Model

Our analysis investigates whether underrepresented groups actively participate in ECF as investors and the factors influencing the amount invested. The setting poses concerns regarding selection and endogeneity. Unobserved individual characteristics may indeed influence (i) the decision to register on the ECF platform and (ii) the decision to invest in the ECF platform, thus introducing bias in our analysis. Specifically, the selection issue can be treated with methods proposed by Heckman (1979), and we account for endogeneity through the use of instrumental variables, akin to the model proposed by Cumming et al. (2019). As a result, we estimate a two-stage selection model with instrumental variables. The first stage models the likelihood that a registered user becomes an investor while treating individual-level demographics as endogenous, while the second stage estimates the investment amount conditional on the decision to invest. We implement this model within a Bayesian framework, using Markov Chain Monte Carlo (MCMC) simulations via random-walk Metropolis-Hastings sampling (Hastings 1970). The Bayesian approach allows us to incorporate external information through prior distributions, which is particularly useful when the sample may not be fully representative or when specific

**TABLE 1** | Variables Description.

| Name | Description |
|---|---|
| Investor | Dummy equal to 1 if an individual registered on the ECF platform has made at least one investment since their registration; 0 otherwise. |
| Investment amount | The amount of the first investment, expressed in thousands of euros. If an individual does not invest, the amount is set to 0 and is excluded from the second stage of the selection model. The natural logarithm is used in the analysis for investors. |
| Female | Dummy equal to 1 if an individual's gender is female; 0 otherwise. |
| Age | The individual's age in years at the time of registration on the ECF platform (only 18 or older). |
| Metropolitan area | Dummy equal to 1 if the individual resides in a metropolitan area, according to the Global MetroMonitor 2020 classification. For Italian cities, the metropolitan areas are Bologna, Florence, Genoa, Milan, Naples, Rome, Turin, and Venice-Padua. (Source: Global Metro Monitor 2020, available at: https://www.brookings.edu/articles/global-metro-monitor). |
| Ethnic minority | Dummy equal to 1 if an individual is classified as belonging to an ethnic minority group (i.e., nonwhite) based on their family name using natural language processing techniques to infer the most likely ethnic origin; 0 otherwise (Source: anonymous data provided by the ECF platform using NamePrism and OpenAI API's GPT-4o-mini model). |
| Higher education | Dummy equal to 1 if an individual has a bachelor's degree, equivalent, or higher degree; 0 otherwise. |
| Entrepreneur or manager | Dummy equal to 1 if an individual is an entrepreneur, or a business manager; 0 otherwise |
| Income | Individual's annual income, constructed as a continuous variable by assigning the mean value of the reported income range. The income categories are: below €10,000; €10,000–€50,000; €50,000–€75,000; €75,000–€100,000; €100,000–€200,000; and above €200,000. For the highest category (above €200,000), we cap the value at €200,000. |
| Competing individuals | The number of other registered individuals when an individual registers on the ECF platform, regardless of their investment decision. The natural logarithm is used in the analysis. |
| GDP per capita | GDP per capita in the NUTS-3 area in which an individual resides. The natural logarithm is used in the analysis. |
| Broadband access | Percentage of households with internet broadband access at the regional level (NUTS-2 level). The data are sourced from Eurostat. |

subgroups are underrepresented. It follows that an important step of these methods lies in the selection of appropriate priors. We follow a standard approach in the literature (e.g., Geweke et al. 2003) combining out-of-sample informative priors based on empirical information on the propensity to register to the platform for the variables of interest with uninformative priors, also known as diffuse priors—modelled as a normal distribution with zero mean and a large standard deviation ~$N(0, 100^2)$— for the other variables (e.g., Sørensen 2007).

Providing the subjectivity in the prior definition, we performed a sensitivity analysis to check the dependence of the results on the choice of a prior. As explained in the introduction, we used secondary data sources to model the demographic distributions of professional investors, namely BAs and VCs. More in detail, concerning the demographics of VCs, we retrieved from the Pitchbook database information on 983 VC managers from VC funds investing in Italy. For BAs, we access data about 1,671 BAs as reported in the 2023 Italian BA report from the Social Innovation Monitor (2023). This allows us to define informative prior distributions for Female, Age, Metropolitan area, and Ethnic minority variables. Table A1 in the Appendix reports the informative priors for VC and BA demographics.

Formally, in the first stage, we examine the factors influencing a registered individual's likelihood of becoming an active investor while controlling for potential endogeneity. For the selection equation, let $i = 1, \ldots, n$ index the individual in the population. The latent propensity to invest is denoted $I_i^*$, which is unobserved. Instead, we observe in our data the binary variable $I_i$ which equals 1 if individual $i$ becomes an investor, and 0 otherwise.

Therefore, we define the following system of equations, which is composed of four equations for the instruments (Equations 1–4), and the latent selection equation (Equation 5):

$$Female = \alpha_{1,0} + \alpha_{1,1} Instrumental\_variables + \delta_1 Z_i + \upsilon_1, \quad (1)$$

$$Age = \alpha_{2,0} + \alpha_{2,1} Instrumental\_variables + \delta_2 Z_i + \upsilon_2, \quad (2)$$

$$Metropolitan\_area = \alpha_{3,0} + \alpha_{3,1} Instrumental\_variables + \delta_3 Z_i + \upsilon_3, \quad (3)$$

$$Ethnic\_minority = \alpha_{4,0} + \alpha_{4,1} Instrumental\_variables + \delta_4 Z_i + \upsilon_4, \quad (4)$$

$$I_i^* = \alpha_{5,0} + \alpha_{5,(1,\ldots 4)} Y_i + \alpha_{5,5} Pr.Investor_i + \delta_5 Z_i + \upsilon_5, \quad (5)$$

where the individual-level demographic characteristics are indicated by $Y_i$ and $Z_i$ are the additional controls. Specifically, in Equations 1–4, *Female, Age, Metropolitan area*, and *Ethnic minority* are treated as endogenous and they are instrumented using the exogenous variable *Broadband access* and the mimicking variables (i.e., *Pr. Female, Pr. Age, Pr. Metropolitan area, Pr. Ethnic minority*), defined in Section 4.2.

To identify the selection equation in Equation (5), we include an exclusion restriction that affects the probability of investing but not the investment amount. Following Cumming et al. (2019) and Rossi et al. (2021), we construct the variable *Pr. Investor* for each observation as the average share of individuals in the same region who made their first investment in the preceding 12 months. This variable captures regional variation in first-time investment activity and reflects the local intensity of investment entry dynamics.

From equation one, we can derive that the likelihood of observing an active investor is therefore:

$$P(I_i = 1) = \Phi(\alpha_{(0,\ldots 4)} Y_i + \alpha_5 Pr.Investor_i + \delta Z_i), \quad (6)$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution.

In the second stage, we model the investment amount, conditional on the decision to invest. The outcome equation is the following:

$$\begin{aligned} Investment\_amount_i = {} & \beta_0 + \beta_1 Female_i + \beta_2 Age_i \\ & + \beta_3 Metropolitan\_area_i \\ & + \beta_4 Ethnic\_minority_i + \beta_5 IMR \\ & + \gamma_1 X_i + \varepsilon_i. \end{aligned} \quad (7)$$

In the outcome equation, the inclusion of the inverse Mills ratio (IMR), which is derived from the first-stage selection model, corrects for potential bias arising from unobserved factors that influence both the likelihood of investing and the investment amount. $X_i$ are additional controls, while $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$ is the error term.

Following the Bayesian approach, the posterior distribution of the unobservable latent variable $y^*$ and parameters $\theta = \{\alpha, \beta, \gamma\}$, are estimated conditional on the observed data $y = \{I_i, Investment\_amount_i\}$ and the priors, as follows:

$$P(I^*, \theta | y) = P(\theta) P(I^*, y | \theta) / P(y) \propto P(\theta) P(I^*, y | \theta). \quad (8)$$

## 5 | Results

### 5.1 | Descriptive Statistics

Table 2 reports the descriptive statistics, with differences in mean values between investors versus non-investors. Of the 20,209 registered individuals on the ECF platform, 14,777 (73.1%) are investors, with an average initial investment of €3,250. Regarding individual demographics, 2440 (12.1%) are female, the average age is 45 years, 7870 (38.9%) resided in metropolitan areas, and 360 (1.8%) were ethnic minority individuals. Regarding controls, 11,625 (57.5%) of individuals hold a higher education degree, 4915 (24.3%) of individuals are entrepreneurs or managers, the average yearly income is €46,030, 7945 is the average number of competing registered investors at the time of registration for each individual, the average GDP per capita at the NUTS-3 level is €36,663, and the broadband access is, on average, 86%.

In the second part of Table 2, we compare investors versus non-investors in ECF. The average initial investment is €4440.

**TABLE 2** | Descriptive statistics.

| *Variables* | All Mean | Median | Std. Dev. | Min | Max | Investor Mean | | Non-investor Mean |
|---|---|---|---|---|---|---|---|---|
| Dependent variables | | | | | | | | |
| Investor (dummy) | 0.73 | 1 | 0.44 | 0 | 1 | 1 | | 0 |
| Investment amount (€, K) | 3.25 | 0.50 | 22.05 | 0 | 1500 | 4.44 | | 0 |
| Explanatory variables | | | | | | | | |
| Female (dummy) | 0.12 | 0 | 0.33 | 0 | 1 | 0.13 | | 0.11 |
| Age (years) | 44.54 | 44 | 12.40 | 18 | 96 | 46.00 | *** | 40.58 |
| Metropolitan area (dummy) | 0.39 | 0 | 0.49 | 0 | 1 | 0.39 | * | 0.37 |
| Ethnic minority (dummy) | 0.02 | 0 | 0.13 | 0 | 1 | 0.02 | | 0.02 |
| *Controls* | | | | | | | | |
| Higher education (dummy) | 0.58 | 1 | 0.44 | 0 | 1 | 0.59 | *** | 0.53 |
| Entrepreneur or manager (dummy) | 0.24 | 0 | 0.43 | 0 | 1 | 0.26 | *** | 0.20 |
| Income (€, K) | 46.03 | 30 | 62.28 | 5 | 200 | 51.74 | *** | 30.47 |
| Competing individuals (no., K) | 7.95 | 8.07 | 4.23 | 0.16 | 14.78 | 7.40 | *** | 9.44 |
| GDP per capita (€, K) | 36.66 | 34.71 | 13.67 | 0.33 | 210.0 | 37.13 | *** | 35.38 |
| Instrumental variable | | | | | | | | |
| Broadband access (%) | 85.56 | 86.58 | 5.05 | 65.24 | 98.60 | 85.25 | *** | 86.40 |
| Observations | 20,209 | | | | | 14,777 | | 5432 |

*Note:* This table reports the descriptive statistics for the population of 20,209 individuals registered on the ECF platform from May 2016 to December 2023. The table also reports the differences in mean values between investors (14,777) versus non-investors (5432). Significance levels for the test on the difference between mean values are based on *t*-test statistics (for continuous and discrete variables) or *z*-test statistics (for dummy variables), when applicable. ***, **, * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Investors are significantly older (46 years vs. 41 years); they are more likely to live in a metropolitan area (39.7% vs. 36.9%); they are more likely to have a higher education degree (59.3% vs. 52.7%); and they are more likely to be entrepreneurs or managers (25.9% vs. 20.1%), compared to non-investors. Investors are more likely to register on the ECF platform when the number of competing registered individuals is lower (7.3k vs. 9.4k), they reside in areas in which GDP per capita is higher (€37.1k vs. €35.4k), and lower broadband access (85.3% vs. 86.4%), compared to non-investors.[6]

Table B1 in reports the correlations between the variables employed in our analysis. The maximum variance inflation factor (VIF) is low enough to indicate that multicollinearity is not a concern for this study.

## 5.2 | Main Results

Table 3 reports the parameters of the Bayesian estimates from the two-stage selection model with instrumental variables, examining the factors that influence the probability of becoming an investor and the amount of initial investment at the investor level. We test the convergence of the Bayesian estimation, which is supported by stable sample paths and low autocorrelation in the Markov chains, indicating reliable posterior inference (Brooks 1998). The low mean square errors (MSE), omitted from the table for conciseness, indicate a good model fit. Specifically, the first stage of the model tests Hypotheses 1a, 2a, 3a, and 4a, while the second stage of the model tests Hypotheses 1b, 2b, 3b, and 4b. In the first stage, in Specifications (1)–(5), we run a system of five equations, where *Female, Age, Metropolitan area* and *Ethnic minority* are endogenously estimated in Specifications (1)–(4) while Specification (5) allow analysis of the selection process on the variable *Investor*. Specification (6) reports the posterior distributions of the second stage. In this model, we incorporate priors using VC demographics on gender, age, and ethnic minority, while uninformative priors for the other variables in the model.

From the first stage Specifications, the instrumental equations show us that *Female*, *Age*, and *Ethnic minority* are positively associated with *Broadband access*, while *Metropolitan area* is negatively affected. Interestingly, the Specifications indicate that individuals' demographics are negatively associated with the mimicking decisions made by previous individuals from the same demographic group in the previous year. Conversely, individuals from ethnic minority groups are more likely to mimic the investment decisions made by others from the same demographic. Concerning the results shown in Specification (5), the posterior mean of *Female* is positive and significant (0.039).[7] Contrary to our expectations, the posterior parameter of *Age* is positive and significant (0.014), showing that an individual's age is positively related to the likelihood of becoming an investor. The posterior mean of *Ethnic minority* is positive and significant (0.152). The posterior mean of *Metropolitan areas* is not significant, suggesting no statistical difference between investors located in metropolitan and rural areas concerning the likelihood of becoming investors. Since the interpretation of economic magnitudes of the coefficients may

**TABLE 3** | Bayesian estimates of the two-stage selection model with instrumental variables using informative priors from VC demographics.

| | (1) First stage Female | | (2) First stage Age | | (3) First stage Metropolitan area | | (4) First stage Ethnic minority | | (5) First stage Investor | | | (6) Second stage Investment amount | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | dF/dX | Std. Dev. | Mean | dF/dX | Std. Dev. |
| Female | | | | | | | | | 0.039 | 0.003 | (0.023)** | 0.006 | 0.004 | (0.002)** |
| Age | | | | | | | | | 0.014 | 0.001 | (0.001)*** | 0.020 | 0.001 | (0.001)*** |
| Metropolitan area | | | | | | | | | −0.073 | −0.005 | (0.061) | 0.073 | 0.005 | (0.020)*** |
| Ethnic minority | | | | | | | | | 0.152 | 0.011 | (0.056)*** | 0.145 | 0.011 | (0.028)*** |
| Higher education | 0.044 | (0.003)*** | −2.443 | (0.111)*** | 0.055 | (0.005)*** | 0.003 | (0.001) | 0.035 | 0.003 | (0.009)*** | 0.081 | 0.006 | (0.009)*** |
| Entrepreneur | −0.046 | (0.003)*** | 1.310 | (0.160)*** | 0.038 | (0.007)*** | 0.002 | (0.001) | 0.075 | 0.005 | (0.017)*** | 0.392 | 0.032 | (0.016)*** |
| Income | −0.019 | (0.001)*** | 3.442 | (0.056)*** | −0.006 | (0.002)*** | −0.003 | (0.001)*** | 0.238 | 0.017 | (0.007)*** | 0.423 | 0.034 | (0.007)*** |
| Competing ind. | 0.007 | (0.003)*** | −0.297 | (0.094)*** | −0.020 | (0.004)*** | −0.012 | (0.001)*** | 0.040 | 0.003 | (0.011)*** | 0.206 | 0.015 | (0.013)*** |
| GDP per capita | −0.025 | (0.005)*** | 0.301 | (0.147)*** | 0.856 | (0.005)*** | −0.018 | (0.001)*** | −0.102 | −0.007 | (0.018)*** | 0.194 | 0.014 | (0.010)*** |
| Broadband access | 0.012 | (0.001)*** | 0.099 | (0.012)*** | −0.037 | (0.001)*** | 0.003 | (0.001)*** | | | | | | |
| Pr. Female | −2.235 | (0.006)*** | 0.459 | (0.352) | 0.210 | (0.004)*** | 0.181 | (0.001)*** | | | | | | |
| Pr. Age | 0.021 | (0.001)*** | −1.174 | (0.017)*** | 0.033 | (0.001)*** | 0.002 | (0.001)*** | | | | | | |
| Pr. Metr. area | 0.004 | (0.004)*** | 123.031 | (0.099)*** | −3.550 | (0.011)*** | −0.242 | (0.001)*** | | | | | | |
| Pr. Ethnic minority | 3.393 | (0.002)*** | −63.649 | (0.311)*** | −1.859 | (0.003)*** | 1.300 | (0.001)*** | | | | | | |
| Pr. Investor | | | | | | | | | 3.417 | | (0.020)*** | | | |
| IMR (Investor) | | | | | | | | | | | | 1.746 | | (0.026)** |
| Year dummies | Yes | | Yes | | Yes | | Yes | | Yes | | | Yes | | |
| Constant | −0.815 | (0.004)*** | 29.518 | (0.105)*** | 0.639 | (0.008)*** | −0.146 | (0.001)*** | −2.505 | | (0.035)*** | −3.269 | | (0.020)*** |
| MCMC iterations | 12,500 | | 12,500 | | 12,500 | | 12,500 | | 12,500 | | | 12,500 | | |
| MCMC sample size | 10,000 | | 10,000 | | 10,000 | | 10,000 | | 10,000 | | | 10,000 | | |
| Burn-in iterations | 2500 | | 2500 | | 2500 | | 2500 | | 2500 | | | 2500 | | |
| Observations | 20,209 | | 20,209 | | 20,209 | | 20,209 | | 20,209 | | | 14,777 | | |
| Log-likelihood | −33,887 | | −33,887 | | −33,887 | | −33,887 | | −33,887 | | | −33,887 | | |

*Note:* This table presents the results from the Bayesian estimates in the parameters from the two-stage model with instrumental variables, examining the factors that influence the investment decision and the amount of initial investment at the investor level. We use the population of 20,209 individuals registered on the ECF platform, and estimates are based on 10,000 simulations of the posterior distribution, while an initial 2,500 simulations are discarded for burn-in. Specifications (1)–(4) are the first stage in which Female, Age, Metropolitan area and Ethnic minority are treated as endogenous and they are instrumented using the exogenous variable *Broadband access* and the mimicking variables (i.e., *Pr. Female, Pr. Age, Pr. Metropolitan area, Pr. Ethnic minority*). Specifications (5)–(6) report the posterior estimates incorporating informative prior distributions on VC demographics on gender, age, and ethnic minority, and all other variables assume uninformative normal distributions. dF/dX is the marginal effect, which is evaluated at the mean of the posterior. The year of the investment is included as fixed-effects. *, **, *** denote that zero is not contained in the 10%, 5% and 1% credible interval, respectively.

not be simple, provided only the discussion on posterior estimates (Sørensen 2007), we compute and report marginal effects evaluated at the posterior means. Specifically, being female is associated with a 0.1 percentage point increase in the probability of becoming an investor, while each additional year of age corresponds to a 0.3 percentage point increase. Belonging to an ethnic minority group shows the largest effect among the three, increasing the likelihood of investment by 1.1 percentage points. Finally, we find evidence that investment decisions are influenced by mimicking the behaviour of previous investors, as testified by the statistical significance of the *Mimicking (Pr. Investor)* variable. Combined, these results support Hypotheses 1a and 4a, while they provide no support for Hypotheses 2a and 3a.

Coming to the second stage model in Specification (6), the posterior mean of *Female* is positive and significant (0.006), which shows that female investors invest more than their counterparts. The posterior mean of *Age* is positive and significant (0.020), indicating that older investors invest more than younger investors, and the posterior mean of *Metropolitan areas* is also positive and significant (0.073). We also find that the posterior mean of *Ethnic minority* is positive and significant (0.145). The marginal effects on the amount invested (in logarithmic value in the regression analyses) indicate distinct associations with individual characteristics. Specifically, being female is associated with an increase of 0.004, age with 0.001, residence in a metropolitan area with 0.005, and ethnic minority status with 0.011. Combined, these results support Hypotheses 1b and 4b, while they provide no support for Hypotheses 2b and 3b.

Concerning control variables, we find evidence that individuals with higher educational levels are more likely to become investors and invest more than individuals with lower educational levels; similarly, entrepreneurs or managers, and individuals with higher income are more likely to become investors and invest more than their counterparts. Furthermore, individuals have a higher probability to become investors and invest more when the competition is higher within the ECF platform, and when they reside in geographical areas with higher GDP per capita. Finally, the estimated coefficient of IMR in the second stage is positive and significant.

In Table 4, we replicate the Bayesian posterior analysis from the parameters in the two-stage selection model, incorporating prior distributions using BA demographics on gender and age, while we incorporate uninformative priors for the other variables in the model. In both stages, we find positive posterior means for *Female*, *Age*, and *Ethnic minority*, while the posterior mean of *Metropolitan area* was not different from zero. Once

**TABLE 4** | Bayesian estimates of the two-stage selection model using informative priors from BA demographics.

| | (1) First stage Investor | | | (2) Second stage Investment amount | | |
|---|---|---|---|---|---|---|
| | **Mean** | **dF/dX** | **Std. Dev.** | **Mean** | **dF/dX** | **Std. Dev.** |
| Female | 0.131 | 0.012 | (0.033)*** | 0.082 | 0.008 | (0.027)*** |
| Age | 0.013 | 0.001 | (0.001)*** | 0.013 | 0.001 | (0.001)*** |
| Metropolitan area | −0.080 | −0.007 | (0.062) | 0.058 | 0.005 | (0.021)*** |
| Ethnic minority | 0.121 | 0.011 | (0.026)*** | 0.189 | 0.018 | (0.024)*** |
| Higher education | 0.081 | 0.007 | (0.019)*** | 0.023 | 0.002 | (0.016) |
| Entrepreneur | 0.001 | 0.000 | (0.022) | 0.344 | 0.035 | (0.019)*** |
| Income | 0.178 | 0.016 | (0.008)*** | 0.351 | 0.034 | (0.007)*** |
| Competing ind. | −0.018 | −0.002 | (0.019) | 0.506 | 0.055 | (0.005)*** |
| GDP per capita | −0.096 | −0.009 | (0.023)*** | 0.109 | 0.010 | (0.011)*** |
| Pr. Investor | 3.483 | 0.682 | (0.035)*** | | | |
| IMR (Investor) | | | | −0.033 | | (0.032) |
| Year dummies | Yes | | | Yes | | |
| Constant | −2.216 | | (0.023)*** | −3.207 | −0.094 | (0.021)*** |
| MCMC iterations | 12,500 | | | 12,500 | | |
| MCMC sample size | 10,000 | | | 10,000 | | |
| Burn-in iterations | 2500 | | | 2500 | | |
| Observations | 20,209 | | | 14,780 | | |
| Log-likelihood | −33,089 | | | −33,089 | | |

*Note:* This table presents the results from the Bayesian estimates in the parameters from the two-stage selection model with instrumental variables, examining the factors that influence the investment decision and the amount of initial investment at the investor level. We use the population of 20,209 individuals registered on the ECF platform, and estimates are based on 10,000 simulations of the posterior distribution, while an initial 2,500 simulations are discarded for burn-in. We omit the first stage in which *Female, Age, Metropolitan area, and Ethnic minority* are treated as endogenous, as included in Table 3. Specifications (1)–(2) report the posterior estimates incorporating informative prior distributions on BA demographics on gender, age, and ethnic minority. All other variables assume uninformative normal distributions. dF/dX is the marginal effect, which is evaluated at the mean of the posterior. The year of the investment is included as fixed-effects. *, **, *** denote that zero is not contained in the 10%, 5% and 1% credible interval, respectively.

again, these findings support Hypotheses 1a, 1b, 4a, and 4b, while we find no support for Hypotheses 2a, 2b, 3a, and 3b. All in all, the consistent evidence for hypotheses 1 and 4 across both VC/BA comparisons supports our findings on both the probability to become an investor and the invested amounts.

### 5.3 | Robustness

To validate the findings reported in Section 5.2, we conduct a series of robustness tests, including alternative prior specifications using demographic data from the geographic population, sensitivity analyses using diffuse priors, and a comparison with the standard economic approach via maximum likelihood estimation.

#### 5.3.1 | Alternative Prior Specification Using Demographic Data From a Geographical Population

Providing the subjectivity in the prior definition, we performed a sensitivity analysis to check the dependence of the results on the choice of a prior. We define a new set of priors using statistics from a more general population demographic. The general population provides a broad societal benchmark, but includes individuals with no interest in equity investment, which may dilute its relevance for our context. For the general population demographics, we use the Italian National Institute of Statistics ISTAT database, considering only the population older than 18 years old. This collection ensures that the data is comprehensive at the NUTS-3 level of statistics, as the national statistics database covers a wide range of demographic, social, and economic variables at the geographical level. This allows us to define informative prior distributions for Female, Age, Metropolitan area, and Ethnic minority variables. Table C1 reports the informative priors for demographic variables by NUTS-3 geographical areas. In Table D1, we replicate the analysis incorporating the priors provided by general population demographics. We find consistent evidence for the results of our main hypotheses, as we find support for Hypotheses 1a and 4a on both the probability of becoming an investor. In Figures 1–4, we provide a graphical representation of the geographical distribution of Italian investors across NUTS-3 regions in Italy. These maps illustrate that the population in our analysis accurately represents the broader Italian population, in alignment with the demographics of interest, that is, gender, age, metropolitan areas, and ethnic minority.

#### 5.3.2 | Alternative Prior Specification Using Diffuse Priors

To test sensitivity to the specification of priors in the main analysis, we replicate our model using only uninformative

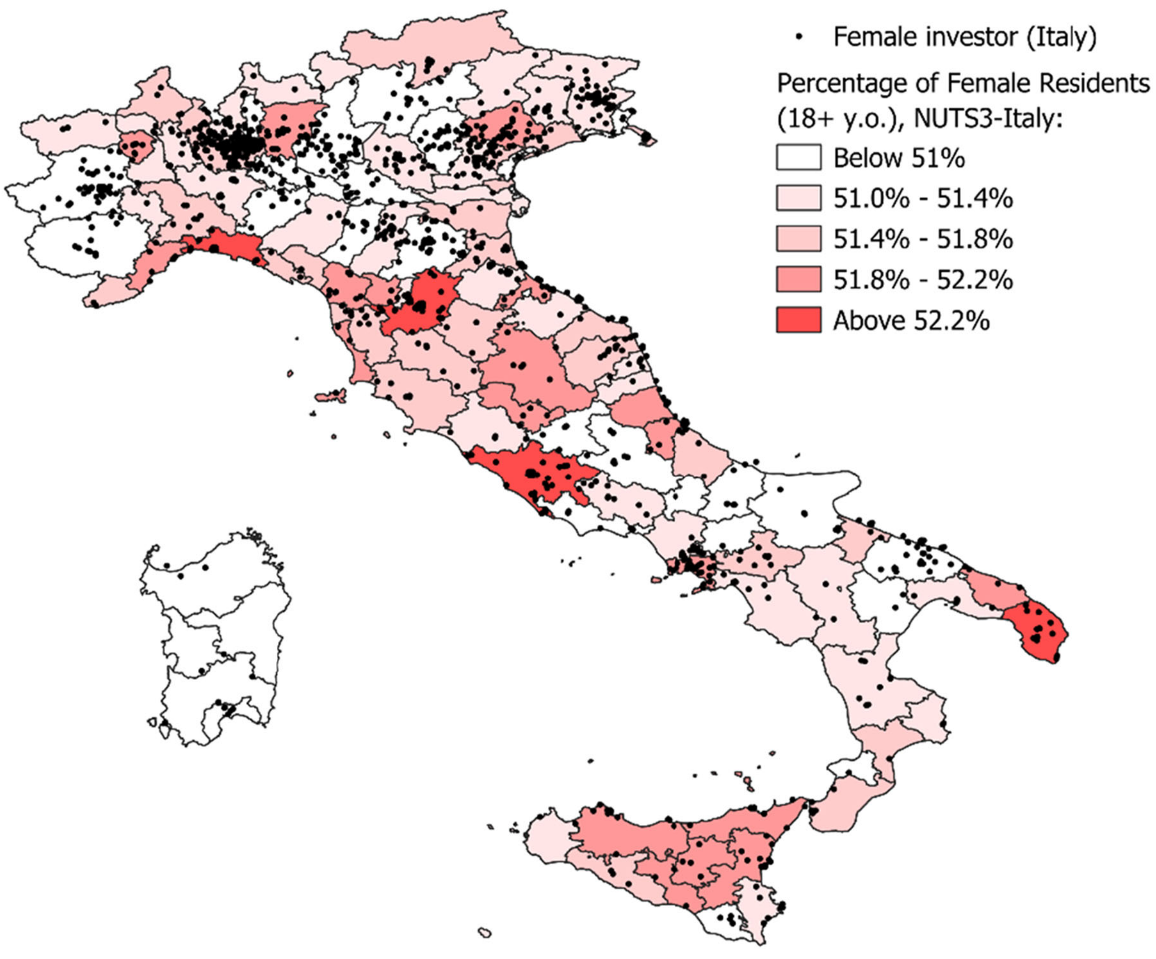


**FIGURE 1** | Female investors. This figure shows active ECF female investors in Italy (2345 obs.), over the map of NUTS-3 regions in Italy by the percentage of female residents (aged 18 and older). [Color figure can be viewed at wileyonlinelibrary.com]

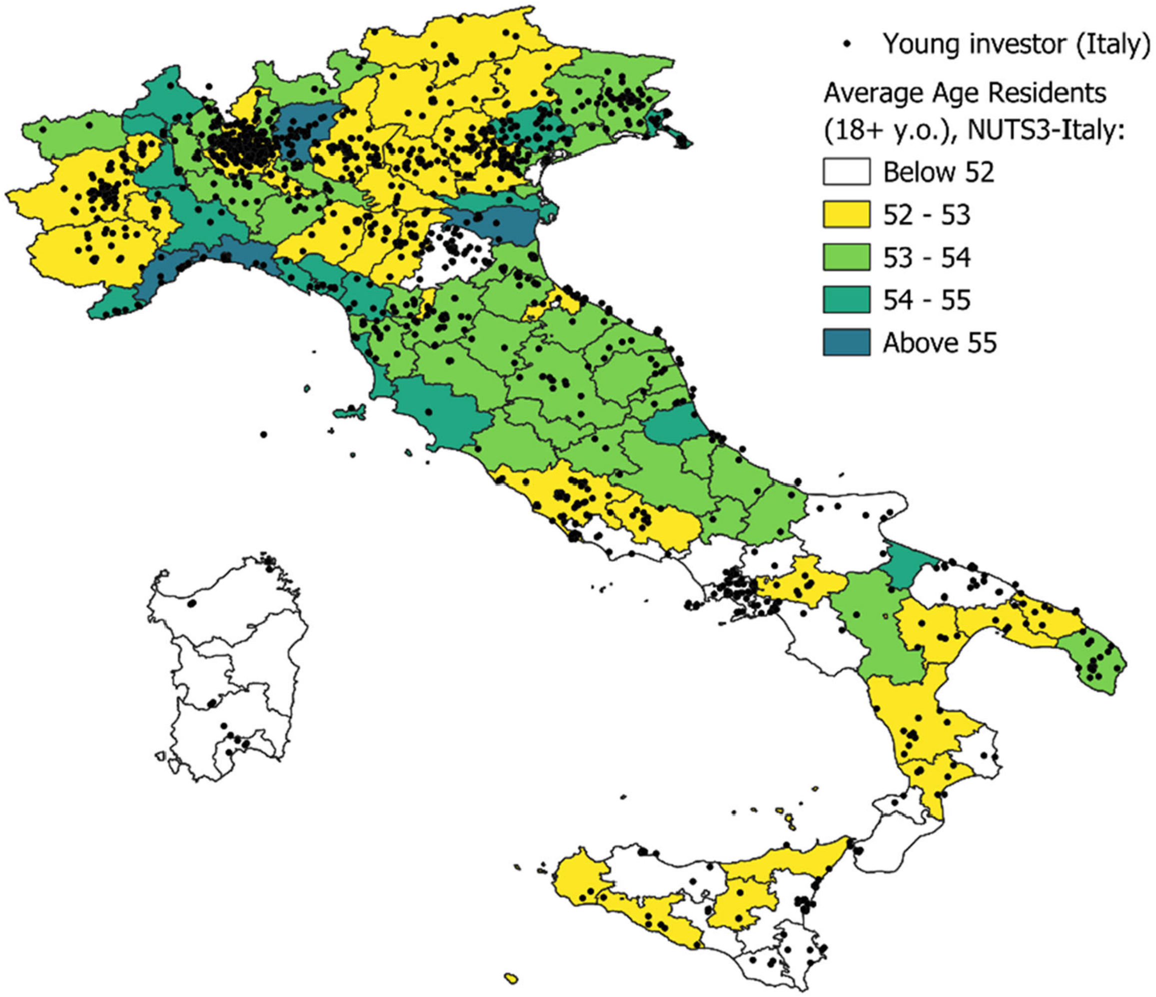


**FIGURE 2** | Young investors. This figure shows active ECF young investors in Italy, aged 30 and below (2569 obs.), over the map of NUTS-3 regions in Italy by age of residents (aged 18 and older). [Color figure can be viewed at wileyonlinelibrary.com]

priors under the assumption of normal distribution. We report the results of the analysis in Table E1. All in all, incorporating uninformative prior specifications leaves the results largely unchanged. The sensitivity analysis indicates that the posterior distributions remain stable under alternative prior specifications, reinforcing the robustness of our findings.

#### 5.3.3 | Alternative Econometric Approach

For comparison of marginal effects, we replicate the two-stage model with instrumental variables fitted using maximum likelihood estimation on the observed data. We report the results of the analysis in Table F1. The coefficients presented in the new model closely align with those in Tables 3 and 4, particularly in terms of sign and statistical significance for *Female, Age*, although we find weaker significance for the coefficients of *Metropolitan area* and *Ethnic minority*. Interestingly, the model estimated via maximum likelihood yields larger marginal effects for *Female*, *Age*, and *Ethnic minority* compared to the Bayesian estimates. This discrepancy suggests that, if one were to interpret the maximum likelihood estimates as causal, it could lead to an overestimation of the true effects.[8] The Bayesian model, by incorporating prior information and regularizing extreme estimates, provides more conservative and stable inference. This highlights the importance of accounting for uncertainty when interpreting marginal effects.

## 6 | Conclusion

This paper provides empirical evidence supporting the role of digital finance in promoting financial inclusivity by expanding investment access to historically underrepresented groups. By shifting the analytical focus from entrepreneurs to investors, our study contributes to the emerging literature on the democratization of entrepreneurial finance, offering one of the first large-scale, investor-level analyses of ECF participation across demographic lines. Using detailed data on over 20,209 individuals registered on Italy's largest ECF platform, we examine whether groups traditionally underrepresented in conventional financial markets exhibit different patterns of participation within the ECF context. Our results show that female and ethnic minority individuals are more likely to invest and tend to commit larger amounts of capital.

Our results contribute to existing research in two important ways. First, we extend the inclusivity debate from the demand

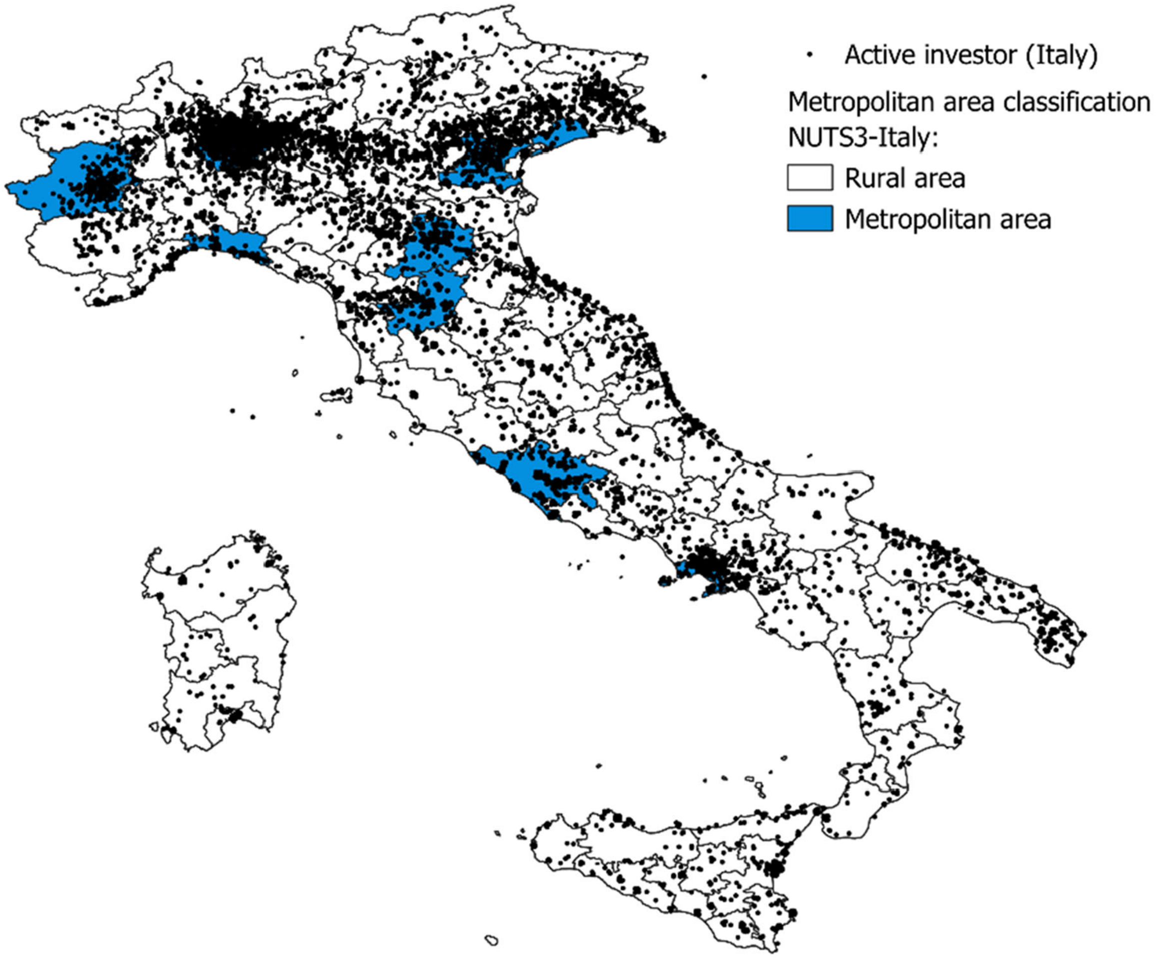


**FIGURE 3** | Investors in metropolitan areas. This figure shows active ECF investors in Italy (14,780 obs.), over the map of NUTS-3 regions in Italy by metropolitan area. [Color figure can be viewed at wileyonlinelibrary.com]

side—entrepreneurs seeking capital—to the supply side, focusing on the individuals who provide capital. This shift offers a more comprehensive understanding of how digital finance reshapes participation dynamics by highlighting who gets to invest, not just who gets funded. Second, while we do not directly compare crowdfunding to traditional financial markets, our within-platform analysis reveals that some of the exclusion penalties typically observed in conventional finance, particularly for women and ethnic minorities, do not appear to persist in the crowdfunding context. This suggests that ECF may represent a more inclusive space for investor participation, especially for historically underrepresented groups.

At the same time, our study has limitations that suggest caution in generalizing the results. The analysis focuses on a single equity crowdfunding platform operating within the Italian market—a valuable setting given Italy's early regulatory adoption of ECF, but one that may limit the external validity of our findings. Institutional frameworks, platform design features, and user demographics may vary significantly across countries and platforms, potentially influencing participation patterns in ways that are context-specific. An interesting avenue for future research is associated with the replication of our analysis in other contexts. An additional avenue for future research would be to more directly compare equity crowdfunding with traditional financial markets, such as venture capital or business angel investments. While our study focuses on within-platform differences among ECF participants, future work could explore whether the patterns of inclusivity observed in crowdfunding are genuinely distinct from those in conventional markets. Such comparisons would provide deeper insight into whether crowdfunding simply reflects broader financial inequalities or actively disrupts them, and under what conditions it does so most effectively.

We believe our findings have important implications for both policy and practice. For policymakers seeking to promote broader financial inclusion, our results suggest that equity crowdfunding can serve as an accessible entry point into early-stage investing for individuals traditionally excluded from venture and angel markets. Supporting regulatory frameworks that reduce administrative friction and encourage platform transparency may further enhance participation. Moreover, platform designers may consider strategies that sustain this inclusivity, such as featuring diverse campaigns, highlighting local projects, or surfacing content that resonates with specific demographic groups. Taken together, our results underscore that while digital finance does not automatically eliminate

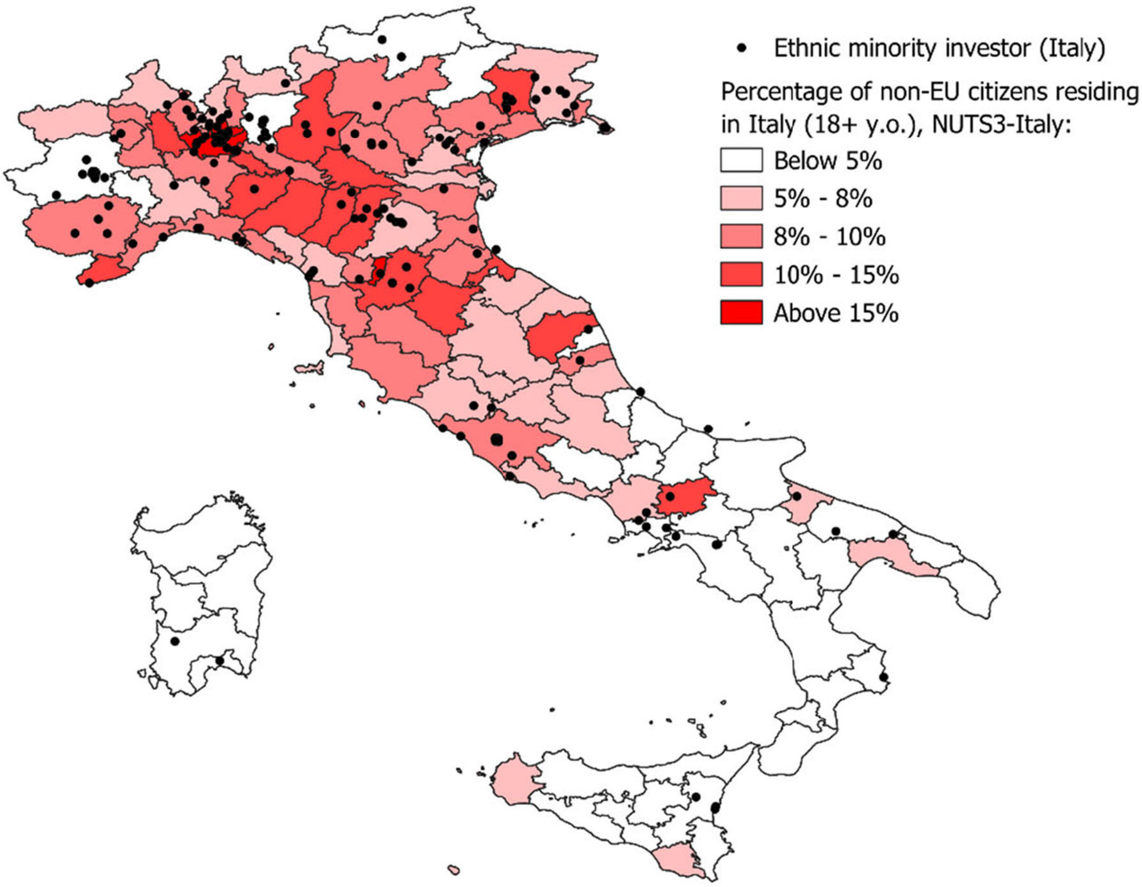


**FIGURE 4** | Ethnic minority investors. This figure shows active ECF ethnic minority investors in Italy (304 obs.), over the map of NUTS-3 regions in Italy by the percentage of non-EU citizens residing in Italy (aged 18 and older). [Color figure can be viewed at wileyonlinelibrary.com]

structural inequalities, it holds significant potential to open new avenues for participation.

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**Consent**

The authors declare no conflicts of interest.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**Data Availability Statement**

The data that has been used is confidential.

**Endnotes**

[1] The Jumpstart Our Business Startups (JOBS) Act, enacted in April 2012, include the Capital Raising Online While Deterring Fraud and Unethical Non-Disclosures Act (CROWDFUND Act), which authorize equity crowdfunding. In October 2015, the Securities and Exchange Commission (SEC) adopted final rules, set to become effective 180 days after publication in the Federal Register. The quotation reported is from the White House Press Release, accessed at https://www.whitehouse.gov/the-press-office/2012/04/05/remarks-president-jobs-act-bill-signing.

[2] Global Metro Monitor 2020, available at: https://www.brookings.edu/articles/global-metro-monitor. For Italian cities, the metropolitan areas are Bologna, Florence, Genoa, Milan, Naples, Rome, Turin, and Venice-Padua.

[3] Ethnic minority is based on natural language processing techniques to infer the most likely ethnic assessed on family names based on the anonymous data provided by the ECF platform and using NamePrism and OpenAI API's gpt-4o-mini model.

[4] Regional statistics on ICT usage in households and by individuals, available at https://ec.europa.eu/eurostat.

[5] Instruments are required to satisfy the validity conditions provided by relevance, exogeneity and excludability. To assess validity, we examine the significance of each instrument by testing the significance of its coefficient in the first-stage regressions. Regarding exogeneity and excludability, we consider our instruments to be fully exogenous, as our probability measures are based on the choices of competing distinct individuals; these measurements are also likely to be excludable.

[6] All the differences reported above are statistically significant at conventional significance levels ($p$-value < 0.01)

[7] From here on, we denote significance for Bayesian estimate when the zero is not contained in the corresponding Bayesian credible interval, following (Sørensen 2007).

[8] Sørensen (2007) suggests that the Bayesian approach provides a more cautious and reliable framework for inference, especially in contexts

affected by endogeneity. His analysis demonstrates that marginal effects estimated using a standard maximum likelihood model can overstate the true effect by up to 90% compared to Bayesian estimates. Consistent with this concern, our robustness analysis shows that relying on a maximum likelihood estimation would overestimate the main effects.

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## Appendix

**TABLE A1** | Prior distributions of VC and BA demographics.

| | VC Mean | Std. Dev. | BA Mean | Std. Dev. |
|---|---|---|---|---|
| Female | 0.2648 | 0.4415 | 0.1400 | 0.3470 |
| Age | 44.9443 | 12.4161 | 52.0000 | 11.1100 |
| Ethnic minority | 0.0157 | 0.1244 | — | — |
| Sample size | 983 | | 1671 | |

*Note:* This table reports demographic statistics for VC from Pitchbook and for BA from the BA Italian Report 2023 from Social Innovation Monitor, Growth Capital & Italian Tech Alliance. The distributions of priors are taken as independent. In line with Geweke et al. (2003), we standardize the covariates and specify $N(0, \sigma^2)$ priors on the regression coefficients. This ensures that priors are appropriately scaled relative to the data. Therefore, for VC demographic we use $N(0, (0.4415)^2)$ for *Female*, $N(0, (12.4161)^2)$ for *Age*, and $N(0, (0.1244)^2)$ for *Ethnic minority*. For BA demographic, we use $N(0, (0.3470)^2)$ for *Female*, $N(0, (11.1100)^2)$ for *Age*. The coefficients are scaled for the selection model relative to these values.

**TABLE B1** | Correlation matrix.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | VIF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Investor | 1.00 | | | | | | | | | | | — |
| (2) Investment amount | 0.03* | 1.00 | | | | | | | | | | 1.25 |
| (3) Female | 0.03* | 0.01 | 1.00 | | | | | | | | | 1.04 |
| (4) Age | 0.19* | 0.22* | 0.07* | 1.00 | | | | | | | | 1.23 |
| (5) Metropolitan area | 0.02* | 0.05* | 0.03* | 0.06* | 1.00 | | | | | | | 1.40 |
| (6) Ethnic minority | 0.00 | 0.01 | 0.03* | −0.05* | 0.00 | 1.00 | | | | | | 1.01 |
| (7) Higher education | 0.06* | 0.05* | 0.05* | −0.05* | 0.11* | 0.00 | 1.00 | | | | | 1.04 |
| (8) Entrepreneur or manager | 0.06* | 0.17* | −0.08* | 0.14* | 0.06* | −0.01 | 0.06* | 1.00 | | | | 1.09 |
| (9) Income | 0.15* | 0.39* | −0.07* | 0.38* | 0.07* | −0.01 | 0.11* | 0.25* | 1.00 | | | 1.41 |
| (10) Competing individuals | −0.22* | 0.17* | 0.07* | −0.11* | −0.02* | 0.03* | −0.02* | −0.05* | −0.04* | 1.00 | | 2.58 |
| (11) GDP per capita | 0.06* | 0.08* | 0.04* | 0.08* | 0.49* | −0.01 | 0.09* | 0.08* | 0.14* | −0.02* | 1.00 | 2.23 |
| (12) Broadband access | −0.10* | 0.15* | 0.07* | −0.02 | 0.09* | 0.05* | 0.00 | 0.00 | 0.06* | 0.68* | 0.44* | 3.19 |
| | | | | | | | | | | | Mean VIF | 1.59 |

*Note:* This table reports the correlation matrix for the population of 20,209 individuals registered on the ECF platform from May 2016 to December 2023. The pairwise significance level at 1% is represented by *. Variance inflation factors (VIFs) are obtained after estimating an OLS regression of *Investor*, including all other variables. VIFs and mean VIFs are low enough to indicate that multicollinearity is not a concern.

**TABLE C1** | Prior distributions of demographics by NUTS-3 Italy.

| | | | Population (M) | Female (%, scale 0-1) | Age (years) | Metropolitan population (%, scale 0-1) | Foreign, non-EU (%, scale 0-1) |
|---|---|---|---|---|---|---|---|
| | | Mean | 0.4678 | 0.5142 | 53.0975 | 0.2865 | 0.0701 |
| | | Variance | 0.2556 | 0.0001 | 1.2726 | 0.0001 | 0.0013 |
| NUTS-1 | NUTS-2 | NUTS-3 | | | | | |
| Areas | Regions | Provinces | | | | | |
| North-West | Piemonte | Torino | 1.887 | 0.519 | 53.676 | 0.038 | 0.062 |
| | | Vercelli | 0.143 | 0.514 | 54.440 | — | 0.083 |
| | | Biella | 0.148 | 0.520 | 55.344 | — | 0.047 |
| | | Verbano-Cusio-Ossola | 0.134 | 0.516 | 54.648 | — | 0.066 |
| | | Novara | 0.310 | 0.514 | 53.115 | — | 0.111 |
| | | Cuneo | 0.492 | 0.507 | 52.892 | — | 0.087 |
| | | Asti | 0.179 | 0.511 | 53.996 | — | 0.081 |
| | | Alessandria | 0.354 | 0.515 | 54.755 | — | 0.078 |
| | Valled'Aosta | Aosta | 0.105 | 0.514 | 53.369 | — | 0.053 |
| | Liguria | Imperia | 0.181 | 0.518 | 54.634 | — | 0.114 |
| | | Savona | 0.234 | 0.522 | 55.482 | — | 0.083 |
| | | Genova | 0.710 | 0.525 | 55.029 | 0.014 | 0.094 |
| | | LaSpezia | 0.186 | 0.517 | 54.607 | — | 0.087 |
| | Lombardia | Varese | 0.746 | 0.516 | 53.081 | — | 0.083 |
| | | Como | 0.508 | 0.511 | 52.710 | — | 0.070 |
| | | Lecco | 0.283 | 0.509 | 53.106 | — | 0.087 |
| | | Sondrio | 0.152 | 0.511 | 53.157 | — | 0.061 |
| | | Bergamo | 0.931 | 0.506 | 51.835 | — | 0.111 |
| | | Brescia | 1.060 | 0.507 | 52.037 | — | 0.113 |
| | | Pavia | 0.462 | 0.512 | 53.240 | — | 0.083 |

(Continues)

| | | | Population (M) | Female (%, scale 0-1) | Age (years) | Metropolitan population (%, scale 0-1) | Foreign, non-EU (%, scale 0-1) |
|---|---|---|---|---|---|---|---|
| | | Lodi | 0.193 | 0.507 | 52.044 | — | 0.101 |
| | | Cremona | 0.301 | 0.509 | 53.137 | — | 0.096 |
| | | Mantova | 0.345 | 0.509 | 52.925 | — | 0.136 |
| | | Milano | 2.746 | 0.517 | 52.144 | 0.055 | 0.173 |
| | | Monza-Brianza | 0.739 | 0.514 | 52.563 | — | 0.170 |
| North-East | Trentino-AltoAdige | Bolzano-Bozen | 0.438 | 0.508 | 50.998 | — | 0.080 |
| | | Trento | 0.457 | 0.511 | 52.230 | — | 0.071 |
| | Veneto | Verona | 0.781 | 0.511 | 52.272 | — | 0.094 |
| | | Vicenza | 0.723 | 0.508 | 52.367 | — | 0.088 |
| | | Belluno | 0.171 | 0.515 | 54.410 | — | 0.064 |
| | | Treviso | 0.741 | 0.510 | 52.605 | — | 0.089 |
| | | Venezia | 0.717 | 0.517 | 53.767 | 0.014 | 0.089 |
| | | Padova | 0.793 | 0.513 | 52.846 | 0.016 | 0.080 |
| | | Rovigo | 0.198 | 0.513 | 54.588 | — | 0.074 |
| | Friuli-Venezia-Giulia | Pordenone | 0.264 | 0.511 | 53.192 | — | 0.102 |
| | | Udine | 0.448 | 0.517 | 54.448 | — | 0.058 |
| | | Gorizia | 0.119 | 0.509 | 54.175 | — | 0.085 |
| | | Trieste | 0.199 | 0.522 | 54.738 | — | 0.091 |
| | Emilia-Romagna | Piacenza | 0.243 | 0.510 | 53.175 | — | 0.111 |
| | | Parma | 0.384 | 0.512 | 52.388 | — | 0.126 |
| | | ReggioEmilia | 0.444 | 0.508 | 52.007 | — | 0.125 |
| | | Modena | 0.596 | 0.511 | 52.478 | — | 0.132 |
| | | Bologna | 0.869 | 0.519 | 52.997 | 0.017 | 0.097 |
| | | Ferrara | 0.296 | 0.518 | 55.018 | — | 0.095 |
| | | Ravenna | 0.331 | 0.515 | 53.837 | — | 0.096 |
| | | Forlì-Cesena | 0.334 | 0.514 | 53.301 | — | 0.091 |
| | | Rimini | 0.290 | 0.520 | 52.954 | — | 0.104 |
| Centre | Toscana | Massa-Carrara | 0.163 | 0.518 | 54.785 | — | 0.052 |
| | | Lucca | 0.329 | 0.519 | 54.107 | — | 0.073 |
| | | Pistoia | 0.249 | 0.520 | 53.805 | — | 0.090 |
| | | Firenze | 0.848 | 0.523 | 53.619 | 0.017 | 0.119 |
| | | Prato | 0.221 | 0.513 | 52.087 | — | 0.193 |
| | | Livorno | 0.282 | 0.520 | 54.664 | — | 0.066 |
| | | Pisa | 0.356 | 0.515 | 53.242 | — | 0.093 |
| | | Arezzo | 0.287 | 0.514 | 53.733 | — | 0.073 |
| | | Siena | 0.223 | 0.518 | 53.896 | — | 0.090 |
| | | Grosseto | 0.188 | 0.518 | 54.853 | — | 0.087 |
| | Umbria | Perugia | 0.545 | 0.520 | 53.724 | — | 0.080 |
| | | Terni | 0.188 | 0.522 | 54.795 | — | 0.068 |
| | Marche | PesaroeUrbino | 0.299 | 0.512 | 53.243 | — | 0.064 |
| | | Ancona | 0.395 | 0.516 | 53.575 | — | 0.079 |
| | | Macerata | 0.259 | 0.515 | 53.660 | — | 0.102 |

(Continues)

TABLE C1 | (Continued)

| | | | Population (M) | Female (%, scale 0-1) | Age (years) | Metropolitan population (%, scale 0-1) | Foreign, non-EU (%, scale 0-1) |
|---|---|---|---|---|---|---|---|
| | | AscoliPiceno | 0.173 | 0.518 | 53.868 | — | 0.125 |
| | | Fermo | 0.144 | 0.513 | 53.713 | — | 0.040 |
| | Lazio | Viterbo | 0.265 | 0.511 | 53.382 | — | 0.061 |
| | | Rieti | 0.131 | 0.503 | 53.722 | — | 0.064 |
| | | Roma | 3.580 | 0.525 | 52.480 | 0.072 | 0.097 |
| | | Latina | 0.478 | 0.508 | 51.957 | — | 0.074 |
| | | Frosinone | 0.397 | 0.511 | 52.944 | — | 0.035 |
| South | Abruzzo | L'Aquila | 0.247 | 0.506 | 53.488 | — | 0.072 |
| | | Teramo | 0.256 | 0.514 | 52.898 | — | 0.075 |
| | | Pescara | 0.265 | 0.522 | 53.049 | — | 0.049 |
| | | Chieti | 0.318 | 0.515 | 53.493 | — | 0.033 |
| | Molise | Isernia | 0.069 | 0.504 | 53.825 | — | 0.038 |
| | | Campobasso | 0.182 | 0.509 | 53.327 | — | 0.032 |
| | Campania | Caserta | 0.749 | 0.514 | 49.903 | — | 0.055 |
| | | Benevento | 0.224 | 0.513 | 52.555 | — | 0.026 |
| | | Napoli | 2.445 | 0.519 | 50.138 | 0.049 | 0.042 |
| | | Avellino | 0.340 | 0.511 | 52.183 | — | 0.030 |
| | | Salerno | 0.892 | 0.514 | 51.633 | — | 0.037 |
| | Puglia | Taranto | 0.471 | 0.518 | 52.682 | — | 0.022 |
| | | Brindisi | 0.323 | 0.521 | 52.738 | — | 0.024 |
| | | Lecce | 0.659 | 0.524 | 53.208 | — | 0.031 |
| | | Foggia | 0.500 | 0.510 | 51.654 | — | 0.034 |
| | | Bari | 1.036 | 0.517 | 52.125 | — | 0.038 |
| | | Barletta-Andria-Trani | 0.318 | 0.510 | 51.025 | — | 0.040 |
| | Basilicata | Potenza | 0.297 | 0.511 | 53.069 | — | 0.022 |
| | | Matera | 0.163 | 0.508 | 52.336 | — | 0.046 |
| | Calabria | Cosenza | 0.570 | 0.513 | 52.395 | — | 0.026 |
| | | Crotone | 0.134 | 0.512 | 51.316 | — | 0.029 |
| | | Catanzaro | 0.289 | 0.515 | 52.462 | — | 0.038 |
| | | ViboValentia | 0.127 | 0.508 | 51.950 | — | 0.030 |
| | | ReggioCalabria | 0.431 | 0.518 | 51.945 | — | 0.041 |
| Islands | Sicilia | Trapani | 0.350 | 0.510 | 52.333 | — | 0.037 |
| | | Palermo | 0.996 | 0.522 | 51.732 | — | 0.026 |
| | | Messina | 0.511 | 0.521 | 52.785 | — | 0.034 |
| | | Agrigento | 0.347 | 0.516 | 52.032 | — | 0.019 |
| | | Caltanissetta | 0.208 | 0.521 | 51.694 | — | 0.022 |
| | | Enna | 0.131 | 0.519 | 52.483 | — | 0.014 |
| | | Catania | 0.888 | 0.519 | 51.224 | — | 0.025 |
| | | Ragusa | 0.266 | 0.503 | 50.816 | — | 0.072 |
| | | Siracusa | 0.323 | 0.511 | 51.886 | — | 0.027 |
| | Sardegna | Sassari | 0.411 | 0.511 | 53.393 | — | 0.020 |
| | | Nuoro | 0.171 | 0.511 | 53.950 | — | 0.019 |

(Continues)

**TABLE C1** | (Continued)

| | Population (M) | Female (%, scale 0-1) | Age (years) | Metropolitan population (%, scale 0-1) | Foreign, non-EU (%, scale 0-1) |
|---|---|---|---|---|---|
| Cagliari | 0.365 | 0.522 | 53.454 | — | 0.044 |
| Oristano | 0.132 | 0.511 | 54.924 | — | 0.012 |
| SudSardegna | 0.292 | 0.506 | 54.721 | — | 0.020 |

*Note:* Statistics from the ISTAT database, considering only the population statistics for individuals or groups of individuals aged 18 years or older.

**TABLE D1** | Bayesian estimates of the two-stage selection model using informative priors from Italian population demographics.

| | (5) First stage Investor | | | (6) Second stage Investment amount | | |
|---|---|---|---|---|---|---|
| | **Mean** | **dF/dX** | **Std. Dev.** | **Mean** | **dF/dX** | **Std. Dev.** |
| Female | 0.021 | 0.002 | (0.016)* | 0.058 | 0.003 | (0.108) |
| Age | 0.015 | 0.001 | (0.001)*** | 0.019 | 0.001 | (0.004)*** |
| Metropolitan area | −0.028 | −0.002 | (0.051) | 0.116 | 0.008 | (0.043)*** |
| Ethnic minority | 0.388 | 0.032 | (0.160)*** | −0.069 | −0.003 | (0.167) |
| Higher education | 0.131 | 0.009 | (0.039)*** | 0.100 | 0.007 | (0.064) |
| Entrepreneur | 0.014 | 0.001 | (0.014) | 0.386 | 0.031 | (0.033)*** |
| Income | 0.212 | 0.015 | (0.027)*** | 0.400 | 0.031 | (0.033)*** |
| Competing ind. | 0.137 | 0.010 | (0.110) | 0.317 | 0.025 | (0.115)*** |
| GDP per capita | −0.153 | −0.011 | (0.042)*** | 0.148 | 0.010 | (0.021)*** |
| Pr. Investor | 3.320 | 0.613 | (0.129)*** | | | |
| IMR (Investor) | | | | 1.163 | | (0.798) |
| Year dummies | Yes | | | Yes | | |
| Constant | −2.537 | | (0.232)*** | −3.244 | −0.070 | (0.028)*** |
| MCMC iterations | 12,500 | | | 12,500 | | |
| MCMC sample size | 10,000 | | | 10,000 | | |
| Burn-in iterations | 2500 | | | 2500 | | |
| Observations | 20,209 | | | 14,780 | | |
| Log-likelihood | −33,089 | | | −33,089 | | |

*Note:* This table presents the results from the Bayesian estimates in the parameters from a two-stage selection model with instrumental variables. Estimates are based on 10,000 simulations of the posterior distribution, while an initial 2500 simulations are discarded for burn-in. All variables assume uninformative normal distributions. The year of the investment is included as fixed-effects. *, **, *** denote that zero is not contained in the 10%, 5% and 1% credible interval, respectively.

**TABLE E1** | Bayesian estimates of the two-stage selection model with instrumental variables using uninformative priors.

| | (1) First stage Female | | (2) First stage Age | | (3) First stage Metropolitan area | | (4) First stage Ethnic minority | | (5) First stage Investor | | | (6) Second stage Investment amount | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **dF/dX** | **Std. Dev.** | **Mean** | **dF/dX** | **Std. Dev.** |
| Female | | | | | | | | | 0.109 | 0.010 | (0.028)*** | 0.160 | 0.015 | (0.045)*** |
| Age | | | | | | | | | 0.014 | 0.001 | (0.001)*** | 0.017 | 0.001 | (0.003)*** |
| Metropolitan area | | | | | | | | | 0.063 | 0.006 | (0.093) | 0.227 | 0.023 | (0.104)*** |
| Ethnic minority | | | | | | | | | 0.152 | 0.015 | (0.029)*** | 0.179 | 0.017 | (0.015)*** |
| Higher education | 0.044 | (0.003)*** | −2.443 | (0.111)*** | 0.055 | (0.005)*** | 0.003 | (0.001) | 0.047 | 0.004 | (0.030)* | 0.011 | 0.001 | (0.017) |
| Entrepreneur | −0.046 | (0.003)*** | 1.310 | (0.160)*** | 0.038 | (0.007)*** | 0.002 | (0.001) | 0.076 | 0.007 | (0.055) | 0.362 | 0.038 | (0.027)*** |
| Income | −0.019 | (0.001)*** | 3.442 | (0.056)*** | −0.006 | (0.002)*** | −0.003 | (0.001)*** | 0.233 | 0.022 | (0.030)*** | 0.430 | 0.045 | (0.045)*** |
| Competing ind. | 0.007 | (0.003)*** | −0.297 | (0.094)*** | −0.020 | (0.004)*** | −0.012 | (0.001)*** | 0.001 | 0.000 | (0.022) | 0.426 | 0.045 | (0.048)*** |
| GDP per capita | −0.025 | (0.005)*** | 0.301 | (0.147)*** | 0.856 | (0.005)*** | −0.018 | (0.001)*** | −0.116 | −0.011 | (0.025)*** | 0.043 | 0.004 | (0.041) |
| Broadband access | 0.012 | (0.001)*** | 0.099 | (0.012)*** | −0.037 | (0.001)*** | 0.003 | (0.001)*** | | | | | | |
| Pr. Female | −2.235 | (0.006)*** | 0.459 | (0.352) | 0.210 | (0.004)*** | 0.181 | (0.001)*** | | | | | | |
| Pr. Age | 0.021 | (0.001)*** | −1.174 | (0.017)*** | 0.033 | (0.001)*** | 0.002 | (0.001)*** | | | | | | |
| Pr. Metr. area | 0.004 | (0.004)*** | 123.031 | (0.099)*** | −3.550 | (0.011)*** | −0.242 | (0.001)*** | | | | | | |
| Pr. Ethnic minority | 3.393 | (0.002)*** | −63.649 | (0.311)*** | −1.859 | (0.003)*** | 1.300 | (0.001)*** | | | | | | |
| Pr. Investor | | | | | | | | | 3.212 | | (0.171)*** | | | |
| IMR (Investor) | | | | | | | | | | | | 1.238 | | (0.748) |
| Year dummies | Yes | | Yes | | Yes | | Yes | | Yes | | | Yes | | |
| Constant | −0.815 | (0.004)*** | 29.518 | (0.105)*** | 0.639 | (0.008)*** | −0.146 | (0.001)*** | −2.188 | | (0.023)*** | −3.294 | | (0.055)*** |
| MCMC iterations | 12,500 | | 12,500 | | 12,500 | | 12,500 | | 12,500 | | | 12,500 | | |
| MCMC sample size | 10,000 | | 10,000 | | 10,000 | | 10,000 | | 10,000 | | | 10,000 | | |
| Burn-in iterations | 2500 | | 2500 | | 2500 | | 2500 | | 2500 | | | 2500 | | |
| Observations | 20,209 | | 20,209 | | 20,209 | | 20,209 | | 20,209 | | | 14,777 | | |
| Log-likelihood | −33,089 | | −33,089 | | −33,089 | | −33,089 | | −33,089 | | | −33,089 | | |

*Note:* This table presents the results from the Bayesian estimates in the parameters of the two-stage selection model with instrumental variables. Estimates are based on 10,000 simulations of the posterior distribution, while an initial simulations are discarded for burn-in. All variables assume uninformative normal distributions. The year of the investment is included as fixed-effect. *, **, *** denote that zero is not contained in the 10%, 5% and 1% credible interval, respectively.

**TABLE F1** | Two-stage model fitted using maximum likelihood estimation.

| | (1) First stage Female | | (2) First stage Age | | (3) First stage Metropolitan area | | (4) First stage Ethnic minority | | (5) First stage Investor | | (6) Second stage Investment amount | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Coeff.** | **Std. Err.** | **Coeff** | **Std. Err.** | **Coeff** | **Std. Err.** | **Coeff** | **Std. Err.** | **Coeff** | **Std. Err.** | **Coeff** | **Std. Err.** |
| Female | | | | | | | | | 0.130 | (0.032)*** | 0.086 | (0.030)*** |
| Age | | | | | | | | | 0.013 | (0.001)*** | 0.013 | (0.001)*** |
| Metropolitan area | | | | | | | | | −0.091 | (0.025)*** | 0.059 | (0.024)** |
| Ethnic minority | | | | | | | | | 0.141 | (0.079)* | 0.180 | (0.074)** |
| Higher education | 0.044 | (0.005)*** | −2.527 | (0.162)*** | 0.055 | (0.006)*** | 0.003 | (0.002) | 0.084 | (0.021)*** | 0.018 | (0.020) |
| Entrepreneur | −0.046 | (0.005)*** | 1.239 | (0.190)*** | 0.028 | (0.007)*** | 0.001 | (0.002) | 0.004 | (0.025) | 0.339 | (0.023)*** |
| Income | −0.019 | (0.002)*** | 3.469 | (0.060)*** | −0.006 | (0.002)*** | −0.003 | (0.001)*** | 0.178 | (0.008)*** | 0.355 | (0.009)*** |
| Competing ind. | 0.007 | (0.023) | −0.223 | (0.791) | −0.020 | (0.029) | −0.011 | (0.009) | −0.022 | (0.087) | 0.496 | (0.068)*** |
| GDP per capita | −0.025 | (0.008)*** | 0.433 | (0.277) | 0.855 | (0.010)*** | −0.018 | (0.003)*** | −0.093 | (0.029)*** | 0.120 | (0.026)*** |
| Broadband access | 0.012 | (0.001)*** | 0.089 | (0.029)*** | −0.037 | (0.001)*** | 0.003 | (0.000)*** | | | | |
| Pr. Female | −2.236 | (0.810)*** | 0.795 | (28.369) | 0.197 | (1.040) | 0.179 | (0.334) | | | | |
| Pr. Age | 0.021 | (0.008)** | −1.173 | (0.293)*** | 0.033 | (0.011)*** | 0.002 | (0.003) | | | | |
| Pr. Metr. area | −1.922 | (0.872)** | 122.967 | (30.539)*** | −3.555 | (1.120)*** | −0.242 | (0.359) | | | | |
| Pr. Ethnic minority | 3.392 | (1.372)** | −63.245 | (48.020) | −1.815 | (1.761) | 1.300 | (0.565)** | | | | |
| Pr. Investor | | | | | | | | | 3.485 | (0.107) | | |
| IMR (Investor) | | | | | | | | | | | −0.004 | (0.069) |
| Year dummies | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| Constant | −0.814 | (0.100)*** | 29.559 | (3.513)*** | 0.637 | (0.129)*** | −0.146 | (0.041)*** | −2.218 | (0.398)*** | −3.243 | (0.311)*** |
| Observations | 20,209 | | 20,209 | | 20,209 | | 20,209 | | 20,209 | | 14,777 | |
| Log-likelihood | −33,225 | | −33,225 | | −33,225 | | −33,225 | | −33,225 | | −33,225 | |

*Note:* This table presents the results from a two-stage selection model with instrumental variables and fitted using maximum likelihood estimation. The table reports the coefficients fitted using the ML estimates, the marginal effect for the selection and outcome equation, and standard errors in parentheses. Specifically, in the first stage, Models (1)–(4) are the instrumental equations in which *Female, Age, Metropolitan area*, and *Ethnic minority* are treated as endogenous using the instrument Broadband access and mimicking variables, respectively. In Model (5), the dependent variable is *Investor* over the predicted values of *Female, Age, Metropolitan area*, and *Ethnic minority*. Finally, in the second stage, Model (6) includes *Investment amount* as the dependent variable, in logarithmic value. All Models include year dummies for fixed effects. ***,**, and * indicate significance at the 1%, 5% and 10% levels, respectively.