J. Int. Financ. Markets Inst. Money 109 (2026) 102326

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Two financial worlds and the bridge between them: profiling crypto, traditional, and dual investors

Paula Lara-Bueno [a], David Tercero-Lucas [a,b,*]

[a] *Comillas Pontifical University – ICADE, Spain*
[b] *Institute for Research in Technology, ICAI School of Engineering, Comillas Pontifical University, Spain*

ARTICLE INFO

JEL Classification:
G11
G41
D14
O33

Keywords:
Cryptocurrency
Stock market
Investors
Financial literacy
Household finance

ABSTRACT

This paper examines whether cryptocurrency investors differ from traditional stock market participants and identifies a third group that combines both asset types. Using data from the 2021 wave of the *Survey of Financial Competencies* conducted by the Bank of Spain, we analyze a nationally representative sample of Spanish households through logistic and multinomial regression models. Results show that crypto investors are more likely to be younger, male, and have lower income and educational attainment. They are also less likely to own pension products or feel confident about their retirement planning compared to stock market investors. In contrast, dual investors—those holding both crypto and traditional assets—exhibit higher financial literacy and greater risk tolerance, but do not differ significantly in income or education from stock investors. Our results reveal the existence of distinct investor profiles and highlight the need for tailored financial education and regulatory approaches that reflect the heterogeneity of market participants.

1. Introduction

Participation in financial markets has been extensively studied in economics and finance. A large body of research links investment decisions to demographic characteristics, risk preferences, financial literacy, and access to information (Campbell, 2006; Guiso et al., 2008). Traditional equity markets have historically been dominated by investors who are older, male, and highly educated (Barber and Odean, 2001; Almenberg and Dreber, 2015), with persistent gender[1] and socioeconomic gaps in participation. The rapid expansion of cryptocurrency markets over the past decade[2] raises the question of whether digital asset investors follow a similar profile or represent a distinct segment of retail participants. Although cryptocurrencies share some features with other risky assets, their technological nature, global accessibility, and relative lower entry barriers may attract investors with different socioeconomic and behavioral characteristics.

A central question is whether cryptocurrency investors differ systematically from participants in traditional equity markets once both groups are observed within the same representative sample. The paper addresses this comparison directly.

* Corresponding author.
E-mail address: dtercero@comillas.edu (D. Tercero-Lucas).

[1] Female investors have consistently been underrepresented in investment activities (Barber and Odean, 2001; Dwyer et al., 2002), particularly in the stock market (Almenberg and Dreber, 2015; Itzkowitz et al., 2023).

[2] See https://coinmarketcap.com for additional details related to cryptocurrency market metrics (prices, market capitalization, and trading volumes) compiled across exchanges.

https://doi.org/10.1016/j.intfin.2026.102326
Received 19 August 2025; Accepted 16 March 2026
1042-4431/

Using nationally representative data[3] for Spain,[4] we examine whether cryptocurrency investors differ systematically from stock market participants when both groups are observed within the same survey framework. The joint observation of traditional and digital asset holdings within a single dataset allows a unified setting for comparative analysis that goes beyond single-market perspectives.[5] Additionally, institutionally variables, seldom available in international studies — such as pension product ownership and retirement planning confidence — are incorporated to capture long-term financial orientation and institutional attachment. Such an approach provides a richer characterization of crypto participation and carries implications for understanding retail portfolio allocation in the digital era, as well as for investor protection and the appropriate regulatory perimeter in crypto markets.

In the baseline analysis, we focus on individuals who invested exclusively in cryptocurrencies or in stocks/shares and estimate logit models with average marginal effects. We then extend the analysis with a multinomial framework that separates stock-only, crypto-only, and dual investors. Our first set of results shows that younger individuals, men, and those with lower income are more likely to invest in cryptocurrencies rather than traditional stock market assets. Our findings align with prior evidence pointing to a less institutionally anchored and more risk-oriented investor segment (Aiello et al., 2023; Almeida and Gonçalves, 2023). However, our analysis adds nuance to this narrative using nationally representative data for Spain and showing that these patterns persist outside the U.S. and Asian contexts studied in earlier research (Fujiki, 2020; Stix, 2021). The results also reveal an important contrast with Aiello et al. (2023). In Spain, crypto-only investors display lower educational attainment than stock investors. The difference reflects both context and comparison: crypto adoption in Spain is concentrated among younger, lower-income individuals, and our benchmark group consists of stock investors rather than the general population. Relative to the population at large, crypto investors may appear highly educated, but compared to stock investors they rank lower. Pension product ownership and confidence in retirement planning are strongly and negatively associated with crypto-only participation, even after extensive controls. This institutional dimension complements standard demographic and risk-based explanations (Jianakoplos and Bernasek, 1998; Agnew et al., 2008; Hastings et al., 2013) and helps reconcile mixed findings in the literature (Lusardi and Mitchell, 2011; Koomson et al., 2023). Additional evidence indicates that risk tolerance matters primarily among younger individuals. Finally, individuals who hold both crypto and traditional assets form a distinct group: although they share the youth and risk appetite of crypto-only investors, they exhibit higher financial literacy and stronger links to conventional financial products. For this segment, exposure to digital assets appears to complement rather than substitute traditional investment strategies.

The findings of this study hold important implications for financial policymakers, investment platforms, and regulatory bodies. Although cryptoasset and securities markets may appear to behave similarly at certain times, the underlying differences in investor profiles call for a differentiated regulatory approach. Treating both markets under the same criteria risks overlooking the specific vulnerabilities of crypto investors, who tend to be younger, less financially experienced, and less institutionally anchored. Uniform regulation could inadvertently expose these individuals to significant losses, fraud, or speculative behavior unsupported by adequate financial knowledge. A tailored framework that accounts for these characteristics is essential to mitigate systemic risk and protect consumers in an environment where digital assets remain highly volatile and less regulated than traditional securities.

Public policy should move beyond generic investor safeguards and adopt measures tailored to the characteristics of crypto participants. Enhanced transparency standards, stricter disclosure requirements, and robust fraud-prevention mechanisms are critical to reducing information asymmetries in digital asset markets. At the same time, education initiatives aimed at younger and less-educated cohorts can help mitigate impulsive decision-making and excessive risk-taking. These programs should emphasize long-term financial planning and portfolio diversification, enabling individuals to integrate crypto holdings responsibly rather than treat them as substitutes for conventional savings. Such interventions not only protect consumers but also strengthen market resilience by promoting informed participation. Recognizing the structural differences between crypto and traditional investors also opens the door to more inclusive financial design. Regulators and financial institutions can leverage these insights to create products and frameworks that accommodate diverse investment behaviors without compromising stability. For example, hybrid solutions that combine digital assets with regulated savings instruments could appeal to dual investors while reinforcing prudent financial practices. Ultimately, a regulatory strategy that balances innovation with consumer protection will foster a secure and equitable financial environment, ensuring that the growth of crypto markets complements rather than undermines the integrity of the broader financial system.

The remainder of the paper is structured as follows. Section 2 presents the literature review and develops the research hypotheses. Section 3 describes the data and outlines the methodological approach. Section 4 reports our empirical results, robustness checks and additional analyses. Section 5 concludes.

[3] We provide the first headtohead comparison for Spain using data from the last wave of the Survey of Financial Competencies – *Encuesta de Competencias Financieras* (ECF) – conducted by the Bank of Spain in 2021, an instrument aligned with OECD/INFE standards and designed to measure financial literacy, financial behavior, and product ownership across demographic groups (Hospido et al., 2023; OECD, 2023). The ECF is a nationally representative dataset uniquely suited for analyzing cryptocurrency adoption alongside traditional investment behavior.

[4] Survey evidence from Funcas indicates that roughly 4 million people in Spain — around 11% of banking consumers — currently own or have previously owned cryptocurrencies. Most report relatively small positions, typically below 5% of their total resources, although a non-negligible minority (about 18%) allocate more than 15% (see https://www.lavanguardia.com/mediterranean/20241202/10162945/4-million-people-spain-cryptocurrencies-funcas-digital-banking-bank-economy-consumer-investment.html).

[5] Although studies such as Fujiki (2020), Stix (2021), Auer and Tercero-Lucas (2022), Aiello et al. (2023), and Colombo and Yarovaya (2024) examine the determinants of cryptocurrency ownership, they do not distinguish investors who combine crypto with traditional assets or analyze how these holdings interact within broader financial strategies.

2. Literature review and hypothesis development

This section reviews the main strands of literature relevant to our study, including work on household finance, the characteristics of cryptocurrency investors, and the international context in which cryptoassets operate. Drawing on these insights, we then outline a set of hypotheses that reflect the theoretical expectations and empirical patterns highlighted in the existing research.

2.1. Literature review

This paper relates to three strands of literature. First, it is closely aligned with the household finance literature on participation in risky asset markets. Prior research has emphasized demographic, behavioral, and cognitive factors as key drivers of market engagement. For example, Campbell (2006) highlights how limited financial sophistication constrains participation in equity markets, particularly among younger and lower-income individuals. Similarly, Guiso and Jappelli (2005) show that trust in financial institutions is a significant determinant of whether households invest in formal markets. Investors in traditional markets are typically older and show a clear preference for financial stability and long-term planning. According to Letkiewicz and Fox (2014), this group tends to accumulate assets gradually, prioritizing diversification and minimizing exposure to unnecessary risks. Moreover, there is a noted underrepresentation of women in this sector, partly due to lower confidence in their financial knowledge, which explains a substantial share of the gender gap in stock market participation alongside differences in actual financial literacy (Bucher-Koenen et al., 2021). The behavior of these investors tends to align with higher financial literacy, which is associated with careful financial analysis, a preference for long-term and sustained returns, and lower engagement in speculative trading (Hastings et al., 2013). Financial intermediation also plays a key role in this profile, as banks and financial advisors help facilitate decision-making and reduce investment uncertainty (Fort et al., 2016). Van Rooij et al. (2011) argue that higher financial literacy substantially increases the likelihood of investing in traditional assets, a view supported by Lusardi and Mitchell (2011) and Hastings et al. (2013), who further link financial knowledge to broader market participation and long-term wealth accumulation. Nevertheless, Fort et al. (2016) caution that education alone may be insufficient in the absence of reliable information channels and transparent banking practices. In this regard, financial literacy not only enhances market participation but also fosters individual financial stability by encouraging retirement planning and the use of advanced financial products (Koomson et al., 2023). Finally, work from Galaasen and Raja (2024) highlights that stock market participation is often short-lived, particularly among households with lower income, wealth, and education levels.

Second, this study connects to the literature on the socioeconomic and psychological characteristics of cryptocurrency investors. A growing body of survey and administrative evidence documents a fairly stable demographic pattern in many jurisdictions: crypto investors are predominantly young men with higher education levels, financial literacy, and a greater willingness to take risks (Henry et al., 2018; Fujiki, 2020; Stix, 2021; Auer and Tercero-Lucas, 2022; Alonso et al., 2023). Wang and Bai (2025) show that both investment experience and financial knowledge are strong predictors of cryptocurrency participation, with the knowledge–investment link being substantially stronger among younger adults aged 18–34. These investors also tend to present greater financial sophistication (Aiello et al., 2023), exhibit higher familiarity with digital tools (Hayashi and Routh, 2025), display strong self-perceived investment expertise and risk tolerance (Colombo and Yarovaya, 2024), and their financial behavior is more driven by speculation and expectations of high short-term returns (Almeida and Gonçalves, 2023). Giudici et al. (2020) point out that many of these investors are motivated by decentralization and the absence of financial intermediaries, which reinforces their perception of autonomy in investment decision-making. Psychological factors play a role, as crypto investors report distinct personality traits, investment behaviors, and higher levels of psychological distress and perceived stress (Kim et al., 2020; Oksanen et al., 2022). Littrell et al. (2024) shows that cryptocurrency ownership is associated with stronger conspiracy beliefs, "dark" personality characteristics, and the use of fringe information ecosystems. While demographic and psychological factors help explain who enters crypto markets, the diffusion patterns documented by Aliu (2024, 2025) suggest that speculative participation can spread endogenously through contagion-like dynamics, highlighting that individual characteristics interact with broader social propagation mechanisms.

Some papers reject the idea of a single "crypto investor type" and document meaningful within–ecosystem segmentation. Evidence on NFT ownership (Balietti et al., 2025) shows a cohort that differs from the broader crypto population along salient margins—age, education, crypto knowledge, and engagement in higher–risk crypto activities such as yield farming or derivatives—suggesting that newer digital–asset submarkets attract distinct investors and can amplify heterogeneity within household portfolios. This pattern aligns with emerging findings on other high–velocity corners of the ecosystem, where participation in speculative submarkets—such as memecoins—appears to be driven less by traditional sociodemographic traits and more by intensive market engagement, short–horizon trading, and elevated risk–taking (Balietti et al., 2026), reinforcing the view that crypto adoption is segmented not only across assets but also across behavioral profiles.

Third, the analysis connects with research at the intersection of crypto finance and international finance that treats cryptoassets as globally priced risky assets traded on integrated venues. Market access typically runs through platforms that serve investors across jurisdictions, and price discovery largely may reflect global risk appetite and international liquidity conditions. Empirical work on Bitcoin's economic role suggests that investment and speculative motives dominate its use over long stretches, so household crypto participation becomes part of households' exposure to internationally traded risk rather than a purely domestic phenomenon (Baur et al., 2018). A related literature studies co-movement and spillovers between crypto returns and traditional asset markets. Evidence documents time variation in correlations and in volatility transmission, with stronger linkages during episodes of stress and rapid repricing (Wu, 2021; Baur and Hoang; 2024). Those findings fit an interpretation in which cryptoassets increasingly load on broad financial conditions, so crypto participation can amplify the sensitivity of household balance sheets to global shocks (IMF, 2023).

Understanding this mechanism is crucial, as it highlights the extent to which digital assets are becoming intertwined with broader financial stability dynamics.

2.2. Hypothesis development

The empirical analysis tests hypotheses that map into a comparison between crypto-only and stock-only investors and a classification that separates stock-only, crypto-only, and dual investors. Building on the three strands of literature reviewed above, this section develops a set of hypotheses regarding the determinants of cryptocurrency versus traditional stock market participation.

Sociodemographic differences. The household finance literature shows that participation in traditional equity markets is strongly shaped by demographic and socioeconomic characteristics: traditional investors tend to be older, more educated, wealthier, and exhibit higher levels of financial literacy and long-term financial planning (Campbell, 2006; Guiso and Jappelli, 2005; Letkiewicz and Fox, 2014), while women participate less frequently, partly due to lower financial confidence (Bucher-Koenen et al., 2021). In contrast, cryptocurrency investors are consistently found to be younger and predominantly male across jurisdictions (Henry et al., 2018; Fujiki, 2020; Stix, 2021), with adoption heavily concentrated among Gen Z and Millennials, whose financial behaviors are shaped by digital nativity, lower trust in institutions, and greater exposure to online information ecosystems (Fujiki, 2020; Hayashi and Routh, 2025). Moreover, recent evidence shows that the relationship between financial knowledge and crypto investment is particularly strong among younger adults (Wang and Bai, 2025), reinforcing a generational divide; accordingly, we expect clear demographic differences between crypto and traditional asset investors.

H1a: *Younger individuals are more likely to invest in cryptocurrencies than in stocks.*

H1b: *Men are more likely than women to invest in cryptocurrencies rather than stocks.*

While demographic predictors such as education and income feature prominently in both the stock market and crypto literatures, the direction of these associations remains ambiguous. Traditional stock investors typically exhibit higher education and higher income (Campbell, 2006; Lusardi and Mitchell, 2011), whereas findings for crypto investors are mixed. Some studies document higher educational attainment and financial sophistication (Henry et al., 2018; Aiello et al., 2023), while others highlight the presence of lower–income and more speculative participants (Almeida and Gonçalves, 2023; Littrell et al., 2024). Given this heterogeneity, we refrain from imposing directional predictions.

H1c. *Educational attainment differs between cryptocurrency and stock investors.*

H1d. *Income levels differ between cryptocurrency and stock investors.*

Financial literacy

Extensive evidence shows that financial literacy is a central determinant of traditional market participation (Van Rooij et al., 2011; Lusardi and Mitchell, 2014). It promotes long–term planning, diversification, and disciplined financial behavior (Hastings et al., 2013; Koomson et al., 2023). Within crypto markets, findings are again mixed: some studies show that crypto investors display relatively high financial knowledge (Henry et al., 2018; Wang and Bai, 2025), whereas others associate lower financial literacy with speculative or short–term–driven crypto adoption (Panos et al., 2020; Stix, 2021). This ambiguity suggests that financial literacy may help differentiate between the two groups, but the expected sign is not theoretically settled. We therefore formulate a directional hypothesis consistent with the view that lower literacy may increase exposure to highly volatile assets:

H2. *Lower financial literacy increases the likelihood of investing in cryptocurrencies rather than in stocks.*

Risk attitudes and long–term financial planning. Crypto investors are consistently found to exhibit higher risk tolerance (Aiello et al., 2023; Colombo and Yarovaya, 2024) and stronger speculative motives (Almeida and Gonçalves, 2023). Conversely, traditional stock investors tend to emphasize long–term planning and institutional forms of saving, including pension products (Letkiewicz and Fox, 2014; Koomson et al., 2023). The absence of intermediaries and the high volatility of crypto assets may also attract individuals less engaged with retirement planning or long–term savings tools. These contrasting behavioral profiles motivate the following hypotheses:

H3a. *Higher willingness to take financial risk increases the probability of investing in cryptocurrencies rather than stocks.*

H3b. *Lower confidence in retirement planning increases the likelihood of investing in cryptocurrencies.*

H3c. *Not holding a pension product increases the probability of investing in cryptocurrencies relative to traditional assets.*

Dual investors and within–ecosystem heterogeneity. Evidence increasingly indicates that crypto investors are not a homogeneous group. Segmentation across NFTs, memecoins, and other high–risk submarkets illustrates substantial differences in sophistication, risk appetite, and digital engagement (Balietti et al., 2025; Balietti et al., 2026). A related emerging pattern is the presence of "dual investors"—those who simultaneously hold cryptocurrencies and traditional financial assets. These individuals may combine characteristics of both worlds. Thus, we posit:

H4. *Dual investors constitute a distinct investor group.*

3. Data and methodology

This section describes the data, variables, and empirical approach used in the analysis. We first outline the construction of the sample based on the Survey of Financial Competencies and explain how investors are classified into crypto, stock, and dual categories. We also detail the financial literacy index and the socioeconomic and behavioral variables included in the models. Finally, we present the logistic and multinomial specifications that form the basis of the empirical analysis.

3.1. The survey of financial competencies

We use the 2021 Survey of Financial Competencies (ECF), conducted by the Bank of Spain. It provides a comprehensive assessment of financial behavior, knowledge, and decision-making among Spanish households. The latest edition was published in 2021 and builds on the 2016 survey. It follows international standards set by the OECD's International Network on Financial Education (INFE), allowing cross-country comparisons (OECD, 2023). The ECF measures financial literacy and examines individuals' familiarity with financial products such as savings, insurance, and credit. It also covers broader aspects of financial decision-making, including cognitive skills and household financial management. The survey captures differences across key demographic groups, including age, gender, income level, and region as well.

The survey established a representative sample of 7,764 individuals aged 18 to 79, selected through a random and stratified sampling method. The ECF ensures a representative sample at both national and regional levels (Hospido et al., 2023), making it a valuable tool for understanding financial behavior in Spain.

3.2. Sample

Our sample is composed of a total of 1,703 individuals.[6] Of these, 1322 individuals have invested in stocks or shares, while 261 have just acquired cryptocurrencies. Additionally, 120 individuals have invested in both types of assets (see second column in Fig. 1).,[78] In the Spanish context, investment in the stock market is more common than in cryptocurrencies, although there is a small group that combines both forms of investment.

In the main analysis, we restrict the sample to individuals who have invested exclusively in either cryptocurrencies or traditional financial assets (stocks or shares), thereby focusing our analysis on the distinct profiles of crypto-only versus stock-only investors and excluding both non-investors and those who hold both asset types.[9]

3.3. Explanatory variables

To characterize and analyze the profiles of cryptocurrency and stock market investors, data have been collected and grouped into three main categories of explanatory variables. First, financial literacy,[10] which plays a key role in investment decision-making, as it influences individuals' ability to assess risk, interpret financial information, and select investment products aligned with their objectives (Koomson et al., 2023). Second, sociodemographic variables are included following the related literature (see Auer and Tercero-Lucas, 2022; Colombo and Yarovaya, 2024). These variables comprise age, gender, educational level, marital status, and income. These characteristics can be decisive in investment choices, as they affect risk perception, investment time horizons, and the willingness to adopt new financial technologies. Moreover, the sociodemographic structure of investors may provide relevant insights into trends in the adoption of cryptocurrencies versus traditional assets. The third category concerns the investor's financial profile, incorporating both decision-making variables and risk preferences. In general, we add variables related to long-term planning and financial autonomy and risk tolerance, which captures each individual's predisposition to take on financial risk, an especially important trait when distinguishing between conservative investors and those willing to engage in higher-volatility assets (Guiso et al., 2018) like cryptocurrencies.

Table 1 reports the definitions and measurement of the financial literacy index, socio-demographic characteristics, and financial profile variables included in the empirical specifications. It documents the coding and scale of each covariate, ensuring transparency regarding the construction of the regression models.

After cleaning the sample and removing observations with inconsistencies in the explanatory variables, the final dataset includes 1464 observations. Among these, 229 individuals (15.6%) are classified as only-crypto investors, while the remaining 1,235 individuals (84.4%) are only-stock investors. Table 2 presents descriptive statistics for the variables included in the baseline

[6] The analysis does not use sample weights, as the final dataset is drawn from a stratified, representative survey of Spanish investors.

[7] To identify individuals who have invested in stocks or shares, we rely on two survey items named QP2_12 and QF3_7. The first, QP2_12, indicates whether the respondent currently holds stocks or shares. The second, QF3_7, captures whether the respondent has saved money via stocks in the past 12 months.

[8] In the case of crypto, we rely on two survey items named QP2_16 and QF3_6. The first, QP2_16, indicates whether the respondent currently holds any cryptocurrency. The second, QF3_6, captures whether the respondent has saved money via cryptocurrencies in the past 12 months.

[9] These individuals will also be part of additional analyses (see Section 3.7). These sample sizes are sufficient for reliable multinomial estimation, reducing concerns about small cell counts.

[10] The financial literacy index was constructed using data from the ECF. The index captures three key dimensions—financial knowledge, behavior, and attitudes—following OECD standards to ensure international comparability. The financial knowledge component reflects the number of correct answers to seven questions on basic concepts such as inflation, compound interest, risk diversification, and the risk-return relationship (range: 0–7). The behavior component assesses the adoption of sound personal finance practices, including budgeting, saving, long-term planning, debt avoidance, and expense tracking (range: 0–9). The attitudes component measures perceptions and predispositions toward saving and spending, based on the average of three statements related to time preference, financial planning, and consumption habits (range: 1–5). The total index score, ranging from 1 to 21, indicates the overall level of financial literacy. For the baseline specification, scores were normalized to a 0–100 scale using a conversion factor of 100/21.

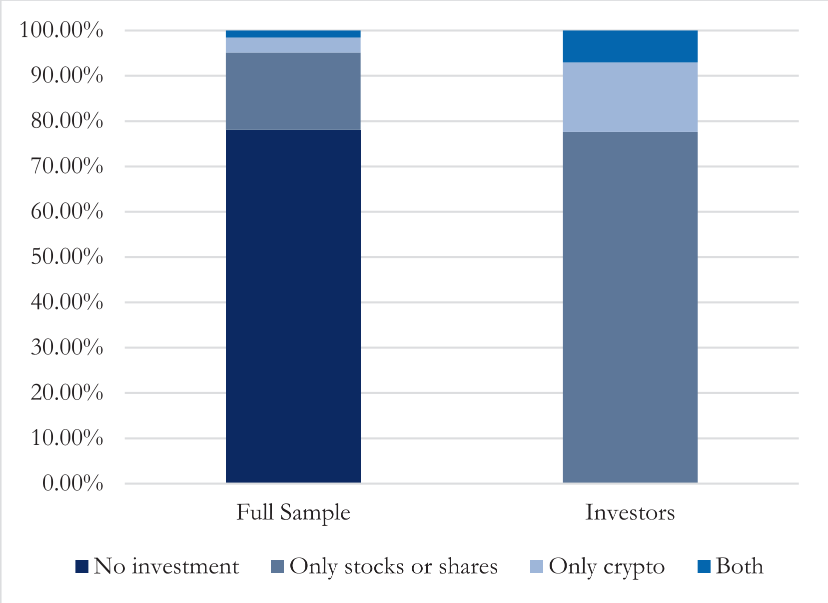


Fig. 1. Distribution of investment profiles. Note: The figure displays the distribution of individuals across four investment categories: non–investors, stock–only investors, crypto–only investors, and dual investors. The data come from the 2021 Survey of Financial Competencies (ECF), using the full representative sample of 7,764 respondents. Among all surveyed individuals, 1,703 report having invested in either traditional financial assets or cryptocurrencies.

Table 1
Description of variables.

Variable	Code	Definition
Dependent variable		
Crypto and stock investors	Crypto_stock	Whether the respondent is a crypto vs being a stock/share investor.
Financial literacy		
Financial literacy	Fin lit	Index measuring the level of basic financial knowledge.
Socioeconomic variables		
Age	Age	Respondent's age in years.
Gender	Gender	Gender (Female/Male).
Educational attainment level	Edu	Educational attainment classification (1–6). See Table A1 in the Appendix.
Income	Income	Income classification (1–3). See Table A2 in the Appendix.
Employed	Employed	Whether the respondent is currently working or not.
Partnered	With partner	Whether the respondent lives with a partner or not.
Investor's financial profile		
Financial decision-making	Fin. decision	Indicates whether the respondent is personally responsible for making day-to-day financial decisions about their own money (Yes/No).
Confidence in pension plan	Pension conf.	Indicates the respondent's self-assessed confidence in having made sound financial plans for retirement (1–5). See Table A3 in the Appendix.
Pension product	Pension prod.	Whether the respondent holds a pension or retirement product (Yes/No).
Risk attitude	Risk	Respondent's willingness to take on financial risk (1–5). See Table A4 in the Appendix.

Note: The table reports the definitions of all variables used in the empirical analysis. The socioeconomic and financial profile indicators follow the classifications of the ECF, including the categorical scales for education, income, retirement confidence, and risk attitude. Financial literacy is measured using the composite index described before. Appendix A provides additional information on some of the variables.

specification.[11]

The average financial literacy score is 70.0 out of 100, indicating a relatively high level of basic financial knowledge. The average age is 49.5 years, and the average education level is 5.0, indicating that most have completed at least upper secondary or university-level studies. The average income falls in the 2.3 category, which corresponds to the range between €15,000 and €47,000 per year. Regarding employment status, 69% report being currently employed, and 68% state that they live with a partner. Only 29% report

[11] Table B.1 in the appendix provides the correlation matrix among all explanatory variables.

Table 2
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Crypto_stock	1464	0.2	0.4	0.0	1.0	1.9	4.6
Fin lit	1,464	70.0	10.1	28.1	93.0	−0.5	3.0
Age	1,464	49.5	14.8	18.0	80.0	−0.1	2.3
Gender	1,464	0.6	0.5	0.0	1.0	−0.5	1.2
Edu	1,464	5.0	1.2	1.0	6.0	−0.8	2.5
Income	1,464	2.3	0.6	1.0	3.0	−0.3	2.3
Employed	1,464	0.7	0.5	0.0	1.0	−0.8	1.7
With partner	1,464	0.7	0.5	0.0	1.0	−0.8	1.6
Fin. decision	1,464	0.3	0.5	0.0	1.0	0.9	1.8
Pension conf.	1,464	3.3	1.2	0.0	5.0	−1.1	4.0
Pension prod.	1,464	0.4	0.5	0.0	1.0	0.2	1.1
Risk	1,464	3.4	1.2	1.0	5.0	−0.6	2.5

Note: The table reports summary statistics for all variables included in the empirical analysis, based on the final sample of 1,464 investors (ECF, year 2021). Reported measures include the number of observations, mean, standard deviation, minimum and maximum values, skewness, and kurtosis.

making financial decisions independently. Finally, 44% of respondents in our sample currently hold a pension product.

3.4. Methodology: logistic regressions

To examine whether cryptocurrency investors differ significantly from traditional stock market participants,[12] we utilize a logistic regression model.

$$Pr(Y_i = 1|X_i) = \Lambda(\beta_0 + \beta_1 F_i + \beta_2 S_i + \beta_3 I_i + \epsilon_i) \tag{1}$$

where $\Lambda(\bullet)$ denotes the standard logistic distribution function. Y_i is a categorical variable that takes the value 1 if individual i owns or owned cryptocurrencies, and 0 if she is a stock market participant. F_i captures our financial literacy variable at individual level, S_i is a vector of socioeconomic variables at individual level, and I_i is a vector of investor financial profile variables at individual level. ϵ_i captures the error term. Standard errors are clustered by individual. The logistic regression model is estimated through maximum likelihood, under the assumption that the error term follows a standard logistic distribution, logistic (0, $\pi^2/3$). Average marginal effects are presented in all regressions unless otherwise indicated.

Logistic regression is appropriate because the dependent variable is binary. The model estimates marginal changes in the probability of crypto investment associated with each covariate. In addition, the logistic link function is well suited for modeling nonlinear relationships between predictors and the probability of choosing one investment type over the other, which aligns with the behavioral nature of our variables. Alternative methods such as linear probability models would impose unrealistic assumptions, including predicted probabilities outside the [0,1] interval.[13]

Likewise, multinomial or ordered models are not appropriate in our baseline setting, as the analysis compares two mutually exclusive categories; the multinomial specification is reserved for the three–group extension presented in Section 4.7. In this section, we investigate whether individuals resemble either of the two single-asset groups or represent a distinct investor segment. A multinomial logit model is suitable for this purpose, as it accommodates multiple, unordered, and mutually exclusive outcomes (see eqs. (2) and (3). The model estimates the relative probability of belonging to each investment group based on individual characteristics, using traditional investors, i.e., stock market investors, as the reference category.

$$Pr(Y_i = j|X_i) = \frac{exp(X_i'\beta_j)}{1 + exp(X_i'\beta_1) + exp(X_i'\beta_2)} \quad for\ j \in \{1, 2\} \tag{2}$$

$$Pr(Y_i = 0|X_i) = \frac{1}{1 + exp(X_i'\beta_1) + exp(X_i'\beta_2)} \tag{3}$$

where Y_i indicates the type of investor (j = 0: traditional (stock-only) investor (reference category); j = 1: cryptocurrency-only investors; j = 2: dual investor (both crypto and stock))., X_i is a vector of individual-level covariates and β_j are the estimated coefficients for each non-reference category j = 1,2, relative to the base outcome j = 0.

[12] It is important to note that this manuscript does not aim to make absolute claims about the education level, income, or any other specific characteristic of cryptocurrency or traditional stock investors in isolation. Rather, our approach focuses on identifying relative differences in individual profiles between the two groups. The results should be interpreted as evidence of statistically significant contrasts in the likelihood of being a crypto versus a stock investor, conditional on the included covariates.

[13] For completeness, and to ensure that our results do not hinge on the choice of the logistic specification, we also estimate the same models using a probit specification and a linear probability model in the robustness checks section.

3.5. Hypothesis-to-test roadmap

To clarify the empirical strategy, we provide a brief roadmap linking hypotheses to the corresponding econometric specifications. Hypotheses H1–H3 are primarily tested using the baseline binary logit models comparing crypto-only and stock-only investors (Table 4). Generational extensions of H1 are examined in Table 5 and Fig. 2. Interaction terms exploring heterogeneous effects related to H2 and H3 are reported in Tables 7 and 8 and Appendix D. Finally, H4 is tested using the multinomial logit specification that distinguishes stock-only, crypto-only, and dual investors (Table 10).

4. Results

This section presents the empirical results of the analysis, starting with individual regressions and progressing to the full set of baseline specifications. We then explore heterogeneity through generational analyses, alternative constructions of risk tolerance, and interaction effects that reveal differences across demographic and behavioral groups. Robustness checks—including bootstrapping, alternative variable definitions, and stricter investor classifications—are also reported to assess the stability of the findings. Additionally, we use a multinomial model to provide new insights into the distinct profile of dual investors, complementing the main binary comparisons.

4.1. Individual regressions

Table 3 reports the preliminary results from individual regressions exploring the relationship between each explanatory variable and the likelihood of being a cryptocurrency investor, relative to being a stock market investor. Lower financial literacy, being older, achieving higher educational attainment, and higher income are all significantly associated with a lower probability of holding crypto assets. Male respondents are significantly more likely to be crypto investors. Being partnered and holding a pension product are also negatively correlated with crypto investment. Confidence in one's pension planning is similarly associated with a lower likelihood of crypto participation. By contrast, a higher willingness to take on financial risk is positively associated with being a crypto investor.

4.2. Baseline results

Table 4 presents the results of estimating eq. (1). Each column corresponds to a different specification with varying sets of explanatory variables.[14] We design several model specifications that selectively exclude variables exhibiting moderate pairwise correlations.[15]

Column (1) includes financial literacy and key socioeconomic variables. Results show that being one year older reduces the probability of investing in cryptocurrencies relative to the stock market by approximately 1 percentage point. This finding supports H1a and confirms that younger individuals are more likely to invest in cryptocurrencies than in stocks. Also, being male increases the likelihood of crypto participation in 3 percentage points compared to investing in the stock market (confirming H1b). Existing literature has already suggested that women generally exhibit more risk-averse financial behavior than men (Agnew et al., 2008; Holden and Tilahun, 2022; Jianakoplos and Bernasek, 1998). Achieving a higher educational attainment is also negatively associated with crypto investment (as H1c suggested) and financial literacy shows a weaker but statistically significant negative association. Panos et al. (2020) argue that higher levels of financial literacy reduce individuals' propensity to engage in risky financial behavior. Aiello et al. (2023) report that crypto investors tend to have higher education levels, whereas our evidence for Spain shows that crypto-only investors have lower educational attainment than stock market participants. The difference partly reflects context. In Spain, crypto adoption is concentrated among younger, lower-income individuals. By contrast, Aiello et al. (2023) analyze a market with greater financial sophistication. The comparison basis also diverges. Aiello et al. (2023) contrast crypto investors with the general population, whereas we compare them directly to stock investors—a group typically more educated and institutionally anchored. Relative to the general population, crypto investors may appear highly educated, but against stock investors they rank lower.

Column (2) focuses on income and household structure, excluding age and education due to potential multicollinearity concerns. Our results show that lower income is strongly associated with a higher probability of crypto investment – hence, the two investor groups are positioned differently along the income distribution, consistent with H1d. These patterns are in line with the findings of Almeida and Gonçalves (2023), who portray cryptocurrency investors as predominantly young males with limited financial resources. Also, individuals not living with a partner are also significantly more likely to invest in crypto.

Column (3) isolates financial profile characteristics, omitting all socioeconomic variables. Self-assessed confidence in having made sound retirement plans, as well as pension product ownership, are strongly associated with a lower likelihood of investing in crypto compared to traditional assets. These findings may highlight a financial behavior more aligned with long-term planning and institutional engagement. Individuals who plan for retirement and participate in formal pension systems tend to prefer lower-volatility, better-regulated assets, and exhibit greater aversion to speculative investments, something consistent with prior research showing

[14] We are aware that the model may exclude relevant behavioral or psychological variables such as overconfidence or time preferences. However, these are not in our dataset.

[15] For instance, we avoid jointly including income with education, pension product ownership, or age, given their respective correlations (see Table B.1). Similarly, age is not included alongside retirement confidence or partnership status in certain specifications.

Table 3
Individual regressions.

	Fin lit	Age	Gender	Edu	Income	Employed
Crypto_stock	−0.002**	−0.011***	0.072***	−0.031***	−0.097***	0.027
	(0.001)	(0.001)	(0.021)	(0.006)	(0.014)	(0.021)
Pseudo R^2	0.017	0.261	0.010	0.013	0.034	0.001
Obs	1,464	1,464	1,464	1,464	1,464	1,464
	With partner	Fin. decision	Pension conf.	Pension prod.	Risk	
Crypto_stock	−0.132***	−0.033	−0.059***	−0.230***	0.043***	
	(0.018)	(0.022)	(0.007)	(0.025)	(0.009)	
Pseudo R^2	0.039	0.001	0.054	0.093	0.019	
Obs	1,464	1,464	1,464	1,464	1,464	

Notes: The table reports the results from individual logistic regressions, where each explanatory variable is entered separately to document its standalone association with the probability of being a cryptocurrency investor. ***, ** and * indicate 1%, 5% and 10% significance levels, respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses, and reported coefficients correspond to average marginal effects. The data come from the 2021 Survey of Financial Competencies.

Table 4
Baseline specification. Crypto vs. stock market investors.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Fin lit	−0.002**	−0.002**		−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Age	−0.010***			−0.009***		−0.009***	−0.009***
	(0.001)			(0.001)		(0.001)	(0.001)
Gender	0.034*	0.080***		0.031*	0.079***	0.044**	0.044**
	(0.017)	(0.020)		(0.018)	(0.020)	(0.018)	(0.018)
Edu	−0.032***			−0.029***		−0.022***	−0.022***
	(0.007)			(0.007)		(0.007)	(0.007)
Income		−0.086***			−0.076***	−0.047***	−0.047***
		(0.016)			(0.015)	(0.014)	(0.014)
Employed	0.020	0.071***		0.033	0.058***	0.036	0.036
	(0.023)	(0.021)		(0.022)	(0.021)	(0.022)	(0.023)
With partner		−0.106***			−0.080***	0.022	0.022
		(0.019)			(0.018)	(0.022)	(0.022)
Fin. decision			−0.017	0.005			0.000
			(0.020)	(0.018)			(0.022)
Pension conf.			−0.038***		−0.048***	−0.013**	−0.013**
			(0.007)		(0.007)	(0.007)	(0.006)
Pension prod.			−0.194***	−0.103***		−0.086***	−0.086***
			(0.024)	(0.020)		(0.021)	(0.021)
Risk			0.040***	0.005	0.033***	0.006	0.006
			(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
Pseudo R^2	0.287	0.081	0.139	0.308	0.130	0.321	0.321
Observations	1,464	1,464	1,464	1,464	1,464	1,464	1,464

Notes: The table presents the results from several logistic regression models comparing cryptocurrency investors to stock market investors. Each column includes different sets of covariates to address potential multicollinearity concerns. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Reported coefficients correspond to average marginal effects. The data come from the 2021 Survey of Financial Competencies.

that retirement planning is positively associated with the accumulation of conventional financial assets and the use of long-term saving products (Lusardi and Mitchell, 2011). Risk tolerance, on the other hand, is positively associated with crypto ownership, aligning with the idea that cryptocurrencies attract individuals more willing to accept financial uncertainty. No significant difference is observed based on whether individuals are personally responsible for everyday financial decisions. Column (4) builds on previous models by incorporating most socioeconomic and behavioral factors, while excluding income and cohabitation status due to multicollinearity concerns. The results confirm previous patterns: individuals with higher education levels and older age are less likely to invest in crypto compared to the stock market, while gender differences persist, with males showing a greater propensity to invest in crypto. The effect of pension product ownership remains strongly negative. In contrast, our results suggest no significant differences in basic financial knowledge (financial literacy) between cryptocurrency investors and traditional stock market participants. Hence, the results do not offer strong support for H2, suggesting that financial literacy is not a robust factor distinguishing crypto and stock investors. A plausible explanation is that both groups may share a baseline level of financial awareness that enables them to navigate investment decisions, even if their asset choices differ. In this sense, financial literacy might represent a necessary threshold rather than a key differentiating factor. It is also conceivable that alternative drivers, such as technological affinity, or speculative appeal, play a more prominent role in shaping cryptocurrency investment behavior, thereby reducing the explanatory role of financial knowledge. Further research is needed to disentangle these mechanisms. Finally, after accounting for age as a continuous variable, the coefficient associated with respondents' risk attitudes loses statistical significance.

Table 5
Generational differences in crypto vs. stock market participation.

	(1)	(2)	(3)	(4)	(5)	(6)
Financial literacy	−0.001	−0.000	0.000	−0.001*	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gen Z	0.238***	0.198***	0.178***			
	(0.027)	(0.029)	(0.031)			
Gen Z & Millennials				0.215***	0.196***	0.189***
				(0.014)	(0.015)	(0.015)
Gender	0.045**	0.058***	0.056***	0.033*	0.042**	0.042**
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
Education	−0.020***	−0.014*	−0.014*	−0.029***	−0.023***	−0.022***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Income		−0.053***	−0.058***		−0.042***	−0.048***
		(0.015)	(0.015)		(0.014)	(0.014)
Employment	0.124***	0.125***	0.128***	0.045**	0.053***	0.060***
	(0.022)	(0.022)	(0.022)	(0.019)	(0.019)	(0.020)
With partner		−0.032*	−0.055**		−0.011	−0.027
		(0.018)	(0.023)		(0.017)	(0.020)
Household decision-maker	0.000		−0.045*	−0.012		−0.037*
	(0.019)		(0.024)	(0.019)		(0.022)
Retirement confidence		−0.026***	−0.025***		−0.020***	−0.019***
		(0.007)	(0.007)		(0.006)	(0.006)
Pension product	−0.185***	−0.150***	−0.144***	−0.131***	−0.107***	−0.103***
	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
Risk attitude	0.027***	0.025***	0.025***	0.015*	0.014*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Pseudo R^2	0.196	0.225	0.228	0.271	0.288	0.290
Observations	1,464	1,464	1,464	1,464	1,464	1,464

Notes: The table re-estimates the baseline model by incorporating generational indicators to test whether younger cohorts are more likely to invest in cryptocurrencies rather than in the stock market. The results are reported across several specifications, with both Gen Z and Millennials examined separately and jointly. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Reported coefficients correspond to average marginal effects. The data come from the 2021 Survey of Financial Competencies.

Column (5) shifts focus back to income and household structure, adding financial profile variables. Column (6) incorporates all variables except being personally responsible for making day-to-day financial decisions – it has a high correlation with variable that controls for living with partner. Column (7) in Table 4 includes all explanatory variables.[16] Results corroborate earlier patterns identified in the preceding specifications: younger individuals, males, those with lower educational attainment and income levels, and those not holding pension products, and those with lower self-assessed confidence in their retirement planning are more likely to invest in cryptocurrencies relative to traditional financial assets. Overall, the evidence offers weak support for H3a and strong support for H3b and H3c, highlighting that weaker long-term financial anchoring more consistently differentiates crypto-only from stock investors than risk preferences alone.

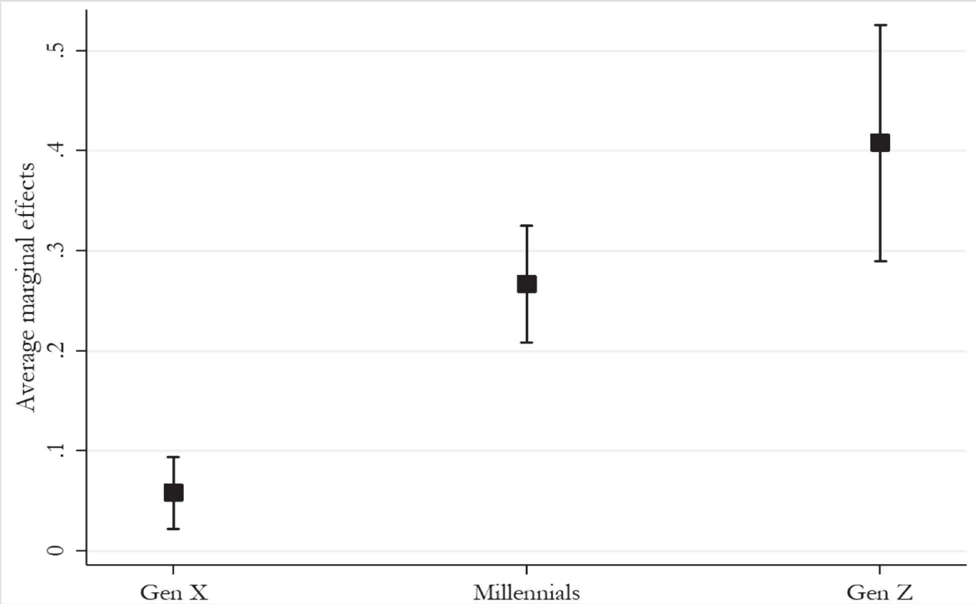
4.3. Generation-based differences[17] in investor profiles

The rapid growth of cryptocurrency markets has been notably driven by younger generations, particularly Gen Z investors, who often exhibit distinct attitudes toward digital technology, decentralization, and financial innovation (Fujiki, 2020). Unlike traditional financial assets, cryptocurrencies have entered the mainstream during the formative financial years of these cohorts, shaping their investment preferences and risk perceptions in ways that may differ from older groups. In order to investigate whether generational factors contribute to the observed patterns in crypto participation, we introduce an indicator for Gen Z respondents (individuals born in 1997 or later), followed by a broader category capturing both Gen Z and Millennials—cohorts whose financial behaviors are likely influenced by the digitalization of finance and post-crisis economic experiences.

Results in Table 5 highlight strong generational differences in investment behavior. Belonging to Generation Z increases the likelihood of investing in cryptocurrencies over traditional stock market assets by approximately 17.8 to 23.8 percentage points, depending on the specification. When Generation Z and Millennials are pooled together, the effect remains robust, ranging from 18.9 to 21.5 percentage points. Therefore, it seems that there is a distinct financial behavior of younger cohorts, who appear more inclined toward emerging digital assets.

[16] To ensure that multicollinearity is not distorting the estimated relationships, we compute variance inflation factors (VIFs) for all explanatory variables. As shown in Table C.1 in the appendix, all values fall well below conventional thresholds.

[17] An exclusively linear approach may overlook behavioral differences across life stages or generational cohorts, as financial attitudes and exposure to crypto assets can vary by age and historical context. To capture potential nonlinearities, we add an additional regression including an age-squared term, though it proves statistically insignificant. Results available upon request.



Note: The figure displays the average marginal effects of belonging to different generational cohorts — Gen X, Millennials, and Gen Z — on the probability of investing in cryptocurrencies versus the stock market, relative to the base category (oldest generation). Each square represents the estimated marginal effect from a logistic regression model controlling for the rest of covariates included in the baseline regression. The vertical lines show 95% confidence intervals. All estimated effects are statistically significant at the 1% level, indicating strong evidence that younger generations are more likely to participate in crypto investment versus the stock market.

Fig. 2. Differential cryptocurrency investment (versus stocks) across generations. Note: The figure displays the average marginal effects of belonging to different generational cohorts — Gen X, Millennials, and Gen Z — on the probability of investing in cryptocurrencies versus the stock market, relative to the base category (oldest generation). Each square represents the estimated marginal effect from a logistic regression model controlling for the rest of covariates included in the baseline regression. The vertical lines show 95% confidence intervals. All estimated effects are statistically significant at the 1% level, indicating strong evidence that younger generations are more likely to participate in crypto investment versus the stock market.

To further examine how investment patterns vary across age groups, we classify individuals into four generational cohorts based on their age at the time of the survey: Gen Z (18–24), Millennials (25–40), Gen X (41–56), and older generation (57 and above). The oldest generation serve as the reference category in the empirical model. The estimated marginal effects in Fig. 2 reveal substantial differences across these groups. Being a member of Generation X increases the probability of investing in cryptocurrencies versus the stock market by approximately 5.8 percentage points relative to the oldest generation, holding all other factors constant. The effect is considerably larger for Millennials, who exhibit a 26.7–percentage–point higher likelihood of crypto investment. The strongest effect is observed among Gen Z (about 40.8 percentage points higher than that of the oldest generation).

The estimates reveal a clear generational pattern. Younger cohorts are consistently more likely to invest in cryptocurrencies than older groups. This result aligns with evidence (Fujiki, 2020; Hayashi and Routh, 2025) showing that digital-native generations display greater familiarity with online financial platforms and a stronger inclination toward emerging financial technologies.

4.4. Alternative specification of risk tolerance

We re-specify the risk tolerance variable as a binary indicator that separates individuals with high levels of risk acceptance from those with more conservative preferences. The upper tercile of the original ordinal distribution is assigned to the high-risk group, while all other values form the reference category. The idea of using a simplified structure is to introduce a sharper conceptual distinction between investors with different risk profiles. Results in Table 6 show that re-specifying risk tolerance as a binary indicator does not alter the overall findings. It remains statistically no significant in the full model once age is included.

Table 6
Binary risk tolerance specification.

	(1)	(2)	(3)	(4)	(5)
Fin lit		−0.001*	−0.001	−0.001	−0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Age		−0.009***		−0.009***	−0.009***
		(0.001)		(0.001)	(0.001)
Gender		0.031*	0.082***	0.043**	0.043**
		(0.020)	(0.018)	(0.018)	(0.018)
Edu		−0.029***		−0.023***	−0.023***
				(0.007)	(0.007)
Income			−0.078***	−0.048***	−0.048***
			(0.016)	(0.014)	(0.014)
Employed		0.033	0.061***	0.037*	0.038
		(0.021)	(0.022)	(0.023)	(0.023)
With partner			−0.082***	0.022	0.022
			(0.018)	(0.019)	(0.022)
Fin. decision	−0.017	0.005			−0.001
	(0.020)	(0.018)			(0.022)
Pension conf.	−0.038***		−0.048***	−0.013**	−0.013**
	(0.007)		(0.007)	(0.006)	(0.006)
Pension prod.	−0.195***	−0.103***		−0.086***	−0.086***
	(0.024)	(0.020)		(0.021)	(0.021)
High risk	0.077***	0.017	0.070***	0.021	0.021
	(0.019)	(0.017)	(0.019)	(0.017)	(0.017)
Pseudo R^2	0.133	0.308	0.128	0.322	0.322
Observations	1,464	1,464	1,464	1,464	1,464

Notes: The table redefines risk tolerance using a binary indicator to distinguish high-risk individuals from others. The alternative specification tests whether a simplified measure produces results consistent with those from the ordinal scale. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Reported coefficients correspond to average marginal effects. The data come from the 2021 Survey of Financial Competencies.

4.5. Exploring the role of interaction terms

The preceding sections estimate the marginal effects of individual characteristics on the probability of investing in cryptocurrencies rather than traditional financial assets. Yet assuming additive and independent effects may overlook important behavioral heterogeneity. Several variables may influence investment decisions differently depending on the respondent's demographic or attitudinal context. We introduce interaction terms to explore whether the effects of selected covariates vary across key subgroups. All specifications retain the same baseline controls to ensure comparability.

Table 7
Marginal effects of risk tolerance on cryptocurrency investment vs. stock market participation across age groups.

Gender	AME
Age (25)	0.056**
	(0.028)
Age (35)	0.025
	(0.016)
Age (45)	0.003
	(0.006)
Age (55)	−0.004
	(0.006)
Age (65)	−0.004
	(0.004)

Notes: The table shows how the marginal effect of risk tolerance on crypto investment varies at selected ages. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Each marginal effect is based on a logit model including the full set of baseline controls (Table 4, column 7) and a single interaction term (age*risk). The data come from the 2021 Survey of Financial Competencies.

4.5.1. Age and risk tolerance

The effect of risk tolerance may not be uniform across the life cycle. Younger individuals are often more exposed to technological innovation and may exhibit greater comfort with high volatile assets such as cryptocurrencies. Older individuals may interpret high risk as a more substantial threat to long-term financial security. Including an interaction between age and risk preference allows us to assess whether the influence of risk tolerance is moderated by life-stage.

We estimate marginal effects of risk preferences at selected ages. Table 7 shows that the effect of risk tolerance concentrates among younger respondents: at age 25, higher risk tolerance is associated with a higher likelihood of crypto investment relative to stock investment, whereas the effect becomes statistically insignificant at older ages.

4.5.2. Gender and risk tolerance

Numerous studies document gender differences in financial behavior, particularly in risk-taking. Women generally exhibit greater financial conservatism and lower willingness to engage in speculative investments (Jianakoplos and Bernasek, 1998; Agnew et al., 2008). Including a gender-by-risk interaction enables us to assess whether risk tolerance has differential marginal effects across men and women, offering insight into gendered behavioral responses in crypto markets.

Table 8 shows the results. The marginal effect of risk tolerance on the likelihood of cryptocurrency investment compared to stock market investment does not differ significantly between men and women, suggesting that gender does not moderate the influence of risk attitudes in shaping preferences between cryptocurrencies and traditional financial assets.

In addition, other interaction terms among potentially relevant variables were explored, but none proved statistically significant. Detailed results are available in Appendix D.

4.6. Robustness checks

4.6.1. Bootstrapped standard errors

We compute bootstrapped standard errors in all specifications to improve the validity of inference. The method relies on repeated resampling of the data (1,000 replications) to approximate the distribution of the estimators without assuming homoskedasticity or asymptotic normality (Horowitz, 2001). It is appropriate for cross-sectional models. Results are robust with respect to the baseline specification.[18]

4.6.2. Different definition of the financial literacy variable

We re-estimate the models using the original definition of the financial literacy variable. The results remain consistent with those obtained in the baseline specification (see Table 9).

4.6.3. More restrictive definition of crypto and stock market investors

Our original investment categories are redefined to include only individuals who currently hold cryptocurrencies or traditional financial assets, rather than those who have merely selected such products in the past year.[19] Results are completely in line with the baseline specification (see Appendix E1).

4.6.4. Linear probability model and probit estimations

We assess whether our baseline logit specification is sensitive to the choice of functional form. To do so, we re-estimate the main model using both a linear probability model and a probit specification. These alternative approaches allow us to verify that our findings are not driven by the particular assumptions of the logistic link function.

Across all specifications, the sign, magnitude, and significance of the key coefficients remain consistent (see Appendix E2), indicating that the results are robust to the use of different binary-response models. Patterns identified in the logit model are not an artifact of the estimation method.

4.7. Further analysis: crypto, stocks… or both?

To capture a more comprehensive view of investment behavior, the analysis expands beyond the binary comparison between cryptocurrency and traditional asset investors. A third category is introduced, comprising individuals who report holding (or have held) both types of financial assets (117 observations in our cleaned sample).[20]

This group matters because joint participation may reflect a different mix of preferences, information, and constraints than participation in a single asset class. We therefore model investor type as a three-way, unordered outcome and employ a multinomial logit specification (see Section 3.3, Eqs. (2) and (3). The model estimates the relative probability of belonging to each investment group based on individual characteristics, using traditional investors, i.e. stock market investors, as the reference category.

[18] Regression results are omitted for brevity but are available upon request.

[19] In the baseline classification, respondents who reported having invested in cryptocurrencies or the stock market may have done so at some point in the past (last year), but this does not necessarily imply that they continued to hold those assets at the time of the survey.

[20] See Appendix F for detailed descriptive statistics for all three investor groups, including means and standard deviations for key demographic, economic, and preference-related variables.

Table 8
Marginal effects of risk tolerance on cryptocurrency investment vs. stock market participation across age groups.

Gender	AME
Male	0.018
	(0.013)
Female	0.001
	(0.010)

Notes: The table presents the marginal effect of risk tolerance separately for men and women. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Each marginal effect is based on a logit model including the full set of baseline controls (Table 4, column 7) and a single interaction term (gender*risk). The data come from the 2021 Survey of Financial Competencies.

Table 9
Alternative definition of financial literacy.

	(1)	(2)	(3)	(4)	(5)	(6)
Alternative financial literacy measure	−0.010**	−0.010**	−0.007*	−0.003	−0.004	−0.004
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Pseudo R^2	0.286	0.081	0.308	0.130	0.321	0.321
Observations	1,464	1,464	1,464	1,464	1,464	1,464

Notes: The table presents the results obtained when replacing the normalized financial literacy index with the original, non–scaled version of the variable. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term and covariates as in columns (1), (2), (4), (5), (6) and (7) in Table 4 respectively. Robust standard errors, clustered at the individual level, are shown in parentheses. Reported coefficients correspond to average marginal effects. The data come from the 2021 Survey of Financial Competencies.

The estimated marginal effects in Table 10 indicate meaningful contrasts across the three investor types.

As the reader can appreciate, crypto-only investors differ clearly from the other groups. They are younger, less educated, and have lower income levels compared to those focused solely on stocks. They also show weaker ties to long-term financial planning: the probability of holding a pension product is significantly lower, and confidence in retirement preparation is reduced. These traits point to a profile less connected to conventional saving frameworks and more oriented toward non-institutional forms of investment.

Dual investors, those who combine both asset types, present a different profile. Although they are also younger, they score higher on financial literacy and report greater willingness to assume financial risk. Men are more likely to appear in this group, confirming patterns found in other studies of crypto adoption (Auer and Tercero-Lucas, 2022). Unlike the crypto-only group, dual investors do not differ significantly in income or education levels from traditional investors, and they are more likely to hold pension products, although the effect is only marginally significant.

The introduction of this third category clarifies whether crypto participation functions as a substitute for traditional finance or as part of a broader investment approach. The evidence suggests that, for a substantial segment of individuals, exposure to digital assets complements rather than replaces conventional financial instruments. Hence, the multinomial specification provides clear evidence in relation to H4. Dual investors do not simply occupy an intermediate position between crypto-only and stock-only participants; instead, they display a distinct combination of demographic and financial characteristics.

5. Conclusion

This paper explores the individual-level characteristics associated with participation in cryptocurrency markets, in contrast to traditional stock market investment. The analysis identifies robust and consistent differences between these investor types across a range of specifications. Individuals who invest in cryptocurrencies exclusively are more likely to be younger, male, and report lower levels of income. They are also significantly less likely to hold pension products or express confidence in their retirement preparedness. The analysis also incorporates a third group of investors who hold both cryptocurrencies and traditional financial assets. These dual investors display a profile that combines elements of both approaches. Like crypto-only investors, they tend to be younger and more tolerant of financial risk. However, they differ in their financial competence and institutional participation. Dual investors exhibit higher levels of financial literacy and are more likely to hold pension products. Their income and education levels do not differ

Table 10
Multinomial logit model (base category: only stock investors).

	Only Crypto	Both Investors
Fin. literacy	−0.001***	0.003***
	(0.001)	(0.001)
Age	−0.007***	−0.004***
	(0.001)	(0.001)
Gender	0.031*	0.038**
	(0.018)	(0.016)
Education	−0.018**	−0.003
	(0.007)	(0.006)
Income	−0.048***	−0.002
	(0.014)	(0.011)
Employed	0.024	0.023
	(0.022)	(0.020)
With partner	0.022	−0.011
	(0.021)	(0.017)
Fin. decision	0.002	−0.012
	(0.021)	(0.017)
Pension conf.	−0.013**	−0.001
	(0.006)	(0.005)
Pension prod.	−0.086***	0.026*
	(0.021)	(0.015)
Risk	0.001	0.018**
	(0.008)	(0.007)

Notes: The table reports marginal effects from a multinomial logit model distinguishing stock-only, crypto-only, and dual investors. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Reported coefficients are average marginal effects from a multinomial logit model in which the dependent variable indicates the type of investor: (0) traditional assets only (reference), (1) cryptocurrencies only, and (2) both. Each column corresponds to one outcome category. Pseudo $R^2 = 0.201$, number of observations = 1,581. The data come from the 2021 Survey of Financial Competencies.

substantially from those of traditional stock market investors. These findings suggest that, for a subset of market participants, cryptocurrency holdings may reflect a strategy of asset diversification rather than a departure from conventional finance.

The presence of distinct investor segments shows that crypto adoption cannot be understood through a single behavioral lens. For some individuals, participation in crypto markets substitutes for access to traditional financial systems, while for others it complements existing investment strategies. Recognizing this diversity is crucial for understanding how digital assets integrate into broader portfolios and for designing effective policy responses. Regulatory frameworks that treat all crypto investors as a homogeneous group risk overlooking these differences, failing to address specific vulnerabilities or behavioral patterns. Likewise, financial education initiatives should go beyond closing knowledge gaps to consider the motivations, time horizons, and risk attitudes that drive early engagement with crypto markets. Tailored interventions that reflect these nuances can promote informed decision-making and support a more balanced and secure integration of digital assets into household finance.

Our findings are rooted in the Spanish context, and this setting shapes how they should be interpreted. Investor profiles depend on institutional arrangements, financial literacy levels, and cultural attitudes toward risk and technology, all of which vary significantly across jurisdictions. Evidence from the United States and Japan (Aiello et al., 2023; Fujiki, 2020) shows that crypto investors often exhibit higher educational attainment, a pattern that contrasts with our observation that crypto-only investors in Spain tend to have lower education levels compared to stock market participants. These discrepancies highlight the importance of both national context and the choice of reference group: comparing crypto investors to the general population, as in Aiello et al. (2023), can lead to different conclusions than comparing them to stock investors, as we do here. Although the empirical analysis focuses on Spain, several of the patterns identified here are likely to extend to other advanced economies. The strong association between youth, risk tolerance, and crypto participation, the existence of a dual segment of investors combining traditional and digital assets, and the weaker institutional anchoring among crypto-only investors—reflected in lower pension product ownership and lower confidence in retirement planning—are consistent with evidence from the United States, Japan, Brazil, and other jurisdictions. These regularities point to behavioral mechanisms that are not confined to a single national setting.

At the same time, certain socioeconomic gradients appear more context dependent. In particular, the income and education gaps observed between crypto-only and stock investors may reflect institutional features specific to Spain, including historically low levels of direct retail participation in equity markets and the distribution of financial literacy across demographic groups. To the best of our knowledge, there is currently no global dataset that combines detailed information on both stock market participants and crypto users, which limits the ability to conduct harmonized cross-country analyses. This gap reinforces the need for caution when extrapolating the Spanish evidence to other countries, as structural and behavioral factors may not align across markets.

Even so, several dynamics plausibly transcend borders because crypto markets operate through cross-border platforms and global price formation. The recurring link between younger age, greater risk tolerance, and crypto activity documented in multiple studies also emerges clearly in our data, suggesting that generational and behavioral drivers travel more easily across jurisdictions than institutional characteristics do. These common elements provide a basis for broader interpretation, but they do not eliminate the importance of local conditions. Regulatory frameworks, access to financial products, trust in institutions, and the baseline level of participation in traditional finance can amplify or attenuate these tendencies. Recognizing both the general and the context-specific components of the results is essential for regulatory design. Investor-protection frameworks in crypto markets should take into account heterogeneous levels of financial experience and long-term financial planning across investor types, and at the same time reflect country-specific institutional baselines that shape retail participation in both traditional and digital financial products. Future research would benefit from harmonized surveys that jointly capture stock and crypto investment behavior across countries, allowing more robust comparisons and a clearer identification of which mechanisms are generalizable and which require tailored policy responses.

Additionally, further work could integrate behavioral and psychological variables not captured in the present analysis, including financial impulsivity, overconfidence, reliance on social media for financial information, and digital familiarity. Expanding the scope to include portfolio composition, transaction frequency, and risk-adjusted performance would also help clarify the role that cryptoassets play in individual financial behavior and the extent to which they reflect structural diversification, speculative tendencies, or behavioral biases.

6. Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this manuscript, the authors used generative AI tools to improve the clarity and readability of the text. The authors reviewed and edited all content generated by these tools and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Paula Lara-Bueno: Writing – original draft, Project administration, Data curation, Formal analysis, Conceptualization. **David Tercero-Lucas:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Additional information

Table A1, A2, A3 and A4, provide the detailed classifications used for educational attainment, income levels, retirement confidence, and risk attitude, respectively.

Table A1
Educational attainment classification.

Category	Interval
1	No formal education
2	Primary school
3	Lower secondary school
4	Upper secondary / high school
5	University-level education
6	Post-graduate education

Note. The table describes the six–level classification used to code respondents' educational attainment in the 2021 Survey of Financial Competencies. Each category corresponds to a clearly defined stage of formal education, ranging from no formal schooling to postgraduate studies.

Table A2
Income classification.

Value	Category	Definition
1	Below €15,000	Estimated to be the 25th centile of the annual gross family income distribution at the time of fieldwork
2	€15,000–€47,000	Estimated to be between the 25th and 75th centiles of the annual gross family income distribution at the time of fieldwork
3	Above €47,000	Estimated to be above the 75th centile of the annual gross family income distribution at the time of fieldwork

Note: The table shows how annual household income is grouped into three categories used in the empirical analysis. Each value corresponds to a specific segment of the income distribution at the time of the 2021 Survey of Financial Competencies, based on percentile cut–offs.

Table A3
Reversed retirement confidence scale.

Value	Interpretation
1	Not at all confident
2	Low confidence
3	Moderate confidence
4	High confidence
5	Very confident

Note: The table details the five–point scale used in the 2021 Survey of Financial Competencies to measure respondents' confidence in their retirement planning after reversing the original coding. Based on the question: "How confident are you that you have done a good job of making financial plans for your retirement?" Original scale: 1 = "Very confident", …, 5 = "Not at all confident". The scale has been reversed so that higher values reflect greater retirement confidence.

Table A4
Reversed risk attitude scale.

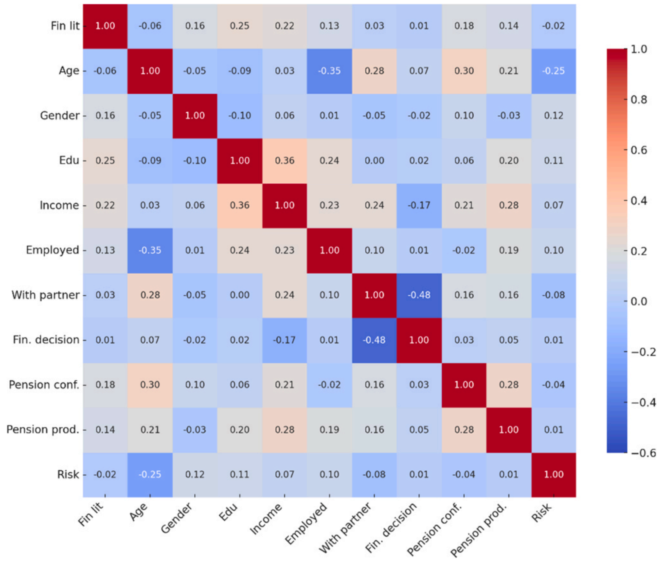
Value	Interpretation
1	Very risk averse
2	Moderately risk averse
3	Neutral
4	Moderately risk tolerant
5	Very risk tolerant

Note: The table outlines the five–level classification of respondents' willingness to take financial risks, after reversing the original 2021 ECF response scale. This variable is derived from the question: "I am prepared to risk some of my own money when saving or making an investment." Original response scale: 1 = "Completely agree", …, 5 = "Completely disagree". The scale has been reversed so that higher values indicate greater willingness to take financial risk.

Appendix B. Correlations

.

Table B.1
Correlation matrix (N = 1,464).



	Fin lit	Age	Gender	Edu	Income	Employed	With partner	Fin. decision	Pension conf.	Pension prod.	Risk
Fin lit	1.00	-0.06	0.16	0.25	0.22	0.13	0.03	0.01	0.18	0.14	-0.02
Age	-0.06	1.00	-0.05	-0.09	0.03	-0.35	0.28	0.07	0.30	0.21	-0.25
Gender	0.16	-0.05	1.00	-0.10	0.06	0.01	-0.05	-0.02	0.10	-0.03	0.12
Edu	0.25	-0.09	-0.10	1.00	0.36	0.24	0.00	0.02	0.06	0.20	0.11
Income	0.22	0.03	0.06	0.36	1.00	0.23	0.24	-0.17	0.21	0.28	0.07
Employed	0.13	-0.35	0.01	0.24	0.23	1.00	0.10	0.01	-0.02	0.19	0.10
With partner	0.03	0.28	-0.05	0.00	0.24	0.10	1.00	-0.48	0.16	0.16	-0.08
Fin. decision	0.01	0.07	-0.02	0.02	-0.17	0.01	-0.48	1.00	0.03	0.05	0.01
Pension conf.	0.18	0.30	0.10	0.06	0.21	-0.02	0.16	0.03	1.00	0.28	-0.04
Pension prod.	0.14	0.21	-0.03	0.20	0.28	0.19	0.16	0.05	0.28	1.00	0.01
Risk	-0.02	-0.25	0.12	0.11	0.07	0.10	-0.08	0.01	-0.04	0.01	1.00

Note: The correlation matrix table reports pairwise correlation coefficients among all explanatory variables used in the baseline analysis. The matrix allows the reader to identify potential linear associations between all variables. Data come from the 2021 Survey of Financial Competencies.

Appendix C. Multicollinearity diagnostics

To assess potential multicollinearity issues among the explanatory variables included in the model, we estimate a linear regression using all covariates and computed the VIFs. Although the main model is a logistic regression, VIFs cannot be calculated directly after nonlinear estimations. Therefore, we use a linear specification solely for diagnostic purposes. Results in Table C1 show that all VIF values are well below the conventional threshold of 5 (O'Brien, 2007), indicating that multicollinearity is not a concern in our empirical specification.

Table C1
Variance Inflation Factors for the independent variables.

Variable	VIF	1/VIF
Age	1.69	0.593
With partner	1.68	0.594
Household decision-maker	1.49	0.673
Employment	1.40	0.714
Income	1.37	0.730
Education	1.30	0.771
Pension product	1.27	0.790
Retirement confidence	1.24	0.808
Financial literacy	1.17	0.854
Risk attitude	1.11	0.900
Gender	1.10	0.911

Note: This table presents the variance inflation factors for all covariates included in the empirical specification. VIF values provide a formal diagnostic for assessing multicollinearity in regression models. Each value reflects how much the variance of a coefficient estimate is inflated due to linear dependence with other predictors. Data come from the 2021 Survey of Financial Competencies.

Appendix D. Additional interaction terms

D.1 Education and financial literacy

Financial literacy and formal education are often correlated, yet they capture distinct aspects of economic competence. Education reflects general cognitive skills and access to formal training, while financial literacy pertains to specific domain knowledge. Including an interaction between the two tests whether the effect of financial literacy is amplified (or diminished) depending on one's educational background. Lusardi and Mitchell (2014) emphasize that low levels of literacy are especially consequential among less-educated individuals.

Table D1
Marginal effects of financial literacy on cryptocurrency investment vs. stock market participation across educational attainment groups.

Gender	AME
No formal education	−0.002
	(0.003)
Primary school	−0.002
	(0.002)
Lower secondary school	−0.001
	(0.006)
Upper secondary / high school	−0.001
	(0.001)
University-level education	−0.001
	(0.001)
Post-graduate education	−0.001
	(0.001)

Notes: The table reports average marginal effects of financial literacy on the probability of being a cryptocurrency investor, evaluated separately for each education level. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Data come from the 2021 Survey of Financial Competencies.

The marginal effect of financial literacy on the likelihood of investing in cryptocurrencies remains negative across all levels of educational attainment. These findings do not support a strong moderating role of formal education in shaping the influence of financial literacy on investment decisions. One potential interpretation is that the specific knowledge captured by financial literacy may operate similarly across educational groups, rather than offering compensatory benefits to less-educated individuals.

D2. Income and risk tolerance.

Higher-income individuals may be more tolerant of financial loss and thus more willing to engage with volatile assets like cryptocurrencies. At the same time, lower-income individuals with high risk tolerance may exhibit different motivations — potentially driven by the appeal of high short-term returns. An interaction between income and risk attitude helps evaluate how financial capacity shapes the behavioral consequences of risk preferences. Our approach helps clarify whether greater risk appetite translates into actual investment behavior differently for those with fewer versus more financial resources. Prior studies have highlighted that risk-taking behavior is shaped not only by preferences but also by the capacity to bear risk (Guiso et al., 2018; Lusardi and Mitchell, 2014).

Table D2
Marginal effects of risk tolerance on cryptocurrency investment vs.stock market participation across income groups.

Gender	AME
Below €15,000	0.016
	(0.020)
€15,000–€47,000	0.006
	(0.009)
Above €47,000	0.001
	(0.012)

Notes: The table presents how the average marginal effect of risk tolerance on crypto investment differs across income categories. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Data come from the 2021 Survey of Financial Competencies.

Results show that the willingness to take financial risk exerts a similar—though statistically imprecise—influence on investment decisions regardless of income tier.

D3. Pension product and risk tolerance.

Holding a pension product may reflect a more conservative long-term planning orientation. If so, risk-tolerant individuals with pension products might still behave more cautiously than equally risk-tolerant peers without such products. We include an interaction that explores whether long-term financial planning tempers the effect of individual risk preferences on asset allocation decisions.

Table D3
Marginal effects of risk tolerance on cryptocurrency investment vs.stock market participation across whether the respondent holds a pension or retirement product.

Gender	AME
Pension product (No)	0.011
	(0.013)
Penson product (Yes)	−0.006
	(0.013)

Notes: The table displays average marginal effects of risk tolerance for individuals who do and do not hold a pension or retirement product. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Data come from the 2021 Survey of Financial Competencies.

Our findings suggest that long-term financial planning, as proxied by pension ownership, does not meaningfully moderate the relationship between risk attitudes and investment in cryptocurrencies.

D4. Age and financial literacy.

The relationship between financial literacy and investment in cryptocurrencies may not be homogeneous across age groups. Younger individuals with high financial literacy might be more inclined to explore innovative or alternative assets like crypto, while older individuals, even if financially literate, might exhibit more conservative preferences due to risk aversion or lifecycle considerations (Lusardi and Mitchell, 2014; Glaser et al., 2014). Interacting age and financial literacy allows us to assess whether the influence of financial knowledge on crypto adoption is moderated by the respondent's stage in life.

However, as Table D4 shows, the marginal effect of financial literacy on the probability of investing in cryptocurrencies does not show meaningful variation across age groups. Knowledge of financial concepts appears to play a similar role across the life cycle in shaping choices between cryptocurrencies and traditional financial assets.

Table D4
Marginal effects of financial literacy on cryptocurrency investment vs. stock market participation across age groups.

Gender	AME
Age (25)	−0.003
	(0.002)
Age (35)	−0.002
	(0.002)
Age (45)	−0.001
	(0.001)
Age (55)	0.000
	(0.001)
Age (65)	0.000
	(0.000)

Notes: This table reports estimated average marginal effects of financial literacy at selected ages. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Data come from the 2021 Survey of Financial Competencies.

Appendix E. Robustness checks

E.1 Restrictive definition of crypto and stock market investors.

Table E1
Refined definitions of investor types.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fin lit	−0.001	−0.001		−0.001	0.000	0.000	0.000
	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Age	−0.012***			−0.010***		−0.010***	−0.010***
	(0.001)			(0.001)		(0.001)	(0.001)
Gender	0.038*	0.092***		0.034***	0.085**	0.045**	0.045**
	(0.020)	(0.023)		(0.020)	(0.020)	(0.020)	(0.020)
Edu	−0.035***			−0.031***	−0.024***	−0.024***	−0.024***
	(0.008)			(0.008)	(0.008)	(0.008)	(0.008)
Income		−0.093***			−0.083***	−0.050***	−0.051***
		(0.018)			(0.018)	(0.016)	(0.016)
Employed	0.008	0.085***		0.021	0.070***	0.026	0.027
	(0.026)	(0.024)		(0.025)	(0.023)	(0.026)	(0.027)
With partner		−0.131***			−0.101***	0.020	0.017
		(0.021)			(0.020)	(0.021)	(0.024)
Fin. decision			−0.028	0.003			−0.006
			(0.023)	(0.020)			(0.024)
Pension conf.			−0.041***		−0.051***	−0.011	−0.011
			(0.008)		(0.008)	(0.007)	(0.007)
Pension prod.			−0.020***	−0.088***		−0.070***	−0.070***
			(0.027)	(0.021)		(0.022)	(0.022)
Risk			0.053***	0.012	0.046	0.013	0.013
			(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
Pseudo R^2	0.306	0.078	0.126	0.321	0.126	0.331	0.331
Observations	1298	1298	1298	1298	1298	1298	1298

Notes: The table presents regression results using a more restrictive classification of crypto and stock market investors, based solely on current holdings rather than past investment activity. Each column corresponds to a different specification that mirrors those used in the baseline models. ***, ** and * indicate 1%, 5% and 10% significance levels respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Reported coefficients correspond to average marginal effects. Data come from the 2021 Survey of Financial Competencies.

E.2 Probit and linear probability model estimations.

Table E2
Alternative binary-response specifications: probit and LPM.

	(1) Probit model	(2) LPM model
Fin lit	−0.001	−0.001
	(0.001)	(0.001)
Age	−0.008***	−0.010***
	(0.001)	(0.001)
Gender	0.046**	0.053***
	(0.018)	(0.017)
Edu	−0.020***	−0.021***
	(0.007)	(0.008)
Income	−0.050***	−0.046***
	(0.014)	(0.017)
Employed	0.023	−0.044*
	(0.023)	(0.023)
With partner	0.020	−0.020
	(0.022)	(0.025)
Fin. decision	−0.002	−0.020
	(0.021)	(0.023)
Retirement	−0.014**	−0.015*
	(0.006)	(0.009)
Pension prod.	−0.077***	−0.081***
	(0.019)	(0.016)
Risk	0.003	0.008
	(0.008)	(0.007)
Pseudo R^2 (probit) / R^2 (LPM)	0.317	0.266
Observations	1,464	1,464

Note: The table reports regression results for two alternative model specifications. Column (1) presents average marginal effects from a logit model, while column (2) reports OLS estimates with robust standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. All models include a constant term (not reported). Robust standard errors, clustered at the individual level, are shown in parentheses. Reported coefficients correspond to average marginal effects. Data come from the 2021 Survey of Financial Competencies.

Appendix F. Descriptive statistics by investor type

.

Table F1
Descriptive statistics by investor type.

Variable	Only Stocks (N = 1235)	Only Crypto (N = 229)	Both (N = 117)
Fin literacy	70.23 (10.05)	68.53 (10.06)	73.79 (9.45)
Age	52.37 (13.54)	34.00 (11.40)	36.09 (11.48)
Gender	0.59 (0.49)	0.72 (0.45)	0.81 (0.39)
Education	5.03 (1.20)	4.68 (1.07)	5.02 (1.12)
Income	2.37 (0.61)	2.08 (0.62)	2.36 (0.59)
Employed	0.68 (0.47)	0.72 (0.45)	0.81 (0.39)
With partner	0.72 (0.45)	0.48 (0.50)	0.50 (0.50)
Fin. decision	0.30 (0.46)	0.25 (0.43)	0.26 (0.44)
Pension conf.	3.41 (1.10)	2.68 (1.31)	3.15 (1.24)
Pension prod.	0.50 (0.50)	0.13 (0.34)	0.37 (0.48)
Risk	3.34 (1.17)	3.74 (1.03)	3.94 (0.86)

Note. The table presents descriptive statistics for key demographic, economic, and preference-related variables across three investor groups: only stocks, only crypto, and both crypto and traditional assets. Values shown are means with standard deviations in parentheses. Data come from the 2021 Survey of Financial Competencies.

Data availability

Data will be made available on request.

References

Agnew, J.R., Anderson, L.R., Gerlach, J.R., Szykman, L.R., 2008. Who chooses annuities? an experimental investigation of the role of gender, framing, and defaults. Am. Econ. Rev. 98 (2), 418–422.

Aiello, D., Baker, S. R., Balyuk, T., Di Maggio, M., Johnson, M. J., and Kotter, J. D. (2023). Who Invests in Crypto? Wealth, Financial Constraints, and Risk Attitudes. *NBER Working Paper*, (31856).

Aliu, F., 2024. Do infectious diseases explain bitcoin price fluctuations? Journal of International Financial Markets. Institutions and Money 93, 102011.

Aliu, F., 2025. Bitcoin as an infectious disease: evidence from SIR epidemiological model. Rev. Behav. Fin. 17 (6), 961–978.

Almeida, J., Gonçalves, T.C., 2023. A systematic literature review of investor behavior in the cryptocurrency markets. J. Behav. Exp. Financ. 37, 100785.

Alonso, S.L., Jorge-Vázquez, J., Rodríguez, P.A., Hernández, B.M.S., 2023. Gender gap in the ownership and use of cryptocurrencies: empirical evidence from Spain. J. Open Innov. Technol. Market Complexity 9 (3–100103).

Auer, R., Tercero-Lucas, D., 2022. Distrust or speculation? the socioeconomic drivers of US cryptocurrency investments. J. Financ. Stab. 62, 101066.

Almenberg, J., Dreber, A., 2015. Gender, stock market participation, and financial literacy. Econ. Lett. 137, 140–142.

Barber, B.M., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. Q. J. Econ. 116 (1), 261–292.

Balietti, S., Celebi, C., Tercero-Lucas, D., 2025. From crypto to NFTs: Identifying the new wave of digital investors. Int. Rev. Financ. Anal. 104, 104172.

Balietti, S., Celebi, C., Pennella, L., and Tercero-Lucas, D. (2026). Meme money, real people: Decoding the crypto memecoin crowd. *SSRN Working Paper* (6021706).

Baur, D.G., Hong, K.H., Lee, A.D., 2018. Bitcoin: Medium of exchange or speculative assets? J. Int. Financ. Mark. Inst. Money 54, 177–189.

Baur, D.G., Hoang, L.T., 2024. Cryptocurrency spillovers and correlations: inefficiency and co-movement. Digit. Finance 6 (2), 203–224.

Bucher-Koenen, T., Alessie, R. J., Lusardi, A., and Van Rooij, M. (2021). Fearless woman: Financial literacy and stock market participation. National Bureau of Economic Research (28723).

Colombo, J. A. and Yarovaya, L. (2024). Are Crypto and Non-crypto Investors Alike? Evidence from a Comprehensive Survey in Brazil. *Technology in Society*, (102468).

Dwyer, P.D., Gilkeson, J.H., List, J.A., 2002. Gender differences in revealed risk taking: evidence from mutual fund investors. Econ. Inq. 40 (3), 486–499.

Campbell, J.Y., 2006. Household finance. J. Financ. 61 (4), 1553–1604.

Fort, M., Manaresi, F., Trucchi, S., 2016. Adult financial literacy and households' financial assets: the role of bank information policies. Econ. Policy 31 (88), 743–782.

Fujiki, H., 2020. Who adopts crypto assets in Japan? evidence from the 2019 financial literacy survey. J. Japanese Int. Econ. 58, 101107.

Galaasen, S. M., and Raja, A. (2024). *The dynamics of stock market participation*. Available at SSRN.

Giudici, G., Milne, A., Vinogradov, D., 2020. Cryptocurrencies: Market analysis and perspectives. J. Industr. Business Econom. 47, 1–18.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). Bitcoin—Asset or Currency? Revealing Users' Hidden Intentions. *ECIS*.

Guiso, L., Jappelli, T., 2005. Awareness and stock market participation. Eur. Finan. Rev. 9 (4), 537–567.

Guiso, L., Sapienza, P., Zingales, L., 2008. Trusting the stock market. J. Financ. 63 (6), 2557–2600.

Guiso, L., Sapienza, P., Zingales, L., 2018. Time varying risk aversion. J. Financ. Econ. 128 (3), 403–421.

Hastings, J.S., Madrian, B.C., Skimmyhorn, W.L., 2013. Financial literacy, financial education, and economic outcomes. Annu. Rev. Econ. 5 (1), 347–373.

Hayashi, F., Routh, A., 2025. Financial literacy, risk tolerance, and cryptocurrency ownership in the United States. J. Behav. Exp. Financ. 101060.

Henry, C.S., Huynh, K.P., Nicholls, G., 2018. Bitcoin awareness and usage in Canada. J. Digit. Banking 2 (4), 311–337.

Horowitz, J. L. (2001). The bootstrap. *Handbook of econometrics*, 5, pp. 3159-3228.

Holden, T.H., Tilahun, M., 2022. Are risk preferences explaining gender differences in investment behavior? J. Behav. Exp. Econ. 101, 101949.

Hospido, L., Machelett, M., Pidkuyko, M., and Villanueva, E. (2023). Encuesta de Competencias Financieras (ECF) 2021: Principales resultados y cambios desde 2016. *Banco de España*.

Imf, 2023. G20 note on the macrofinancial implications of crypto assets. IMF Staff Note.

Itzkowitz, J., Itzkowitz, J., and Schwartz, A. (2023). The Gender Gap in Stock Market Participation: Evidence from Stock Gifting. *Available at SSRN 4539694*.

Jianakoplos, N.A., Bernasek, A., 1998. Are women more risk averse? Econ. Inq. 36 (4), 620–630.

Kim, H.J., Hong, J.S., Hwang, H.C., Kim, S.M., Han, D.H., 2020. Comparison of psychological status and investment style between bitcoin investors and share investors. Front. Psychol. 11, 502295.

Koomson, I., Villano, R.A., Hadley, D., 2023. The role of financial literacy in households' asset accumulation process: evidence from Ghana. Rev. Econ. Househ. 21 (2), 591–614.

Letkiewicz, J., Fox, J., 2014. Conscientiousness, financial literacy, and financial behavior. J. Consum. Aff. 48 (2), 274–300.

Littrell, S., Klofstad, C., Uscinski, J.E., 2024. The political, psychological, and social correlates of cryptocurrency ownership. PLoS One 19 (7), e0305178.

Lusardi, A., and Mitchell, O. S. (2011). Financial literacy and planning: Implications for retirement wellbeing. *National Bureau of Economic Research* (17078).

Lusardi, A., Mitchell, O.S., 2014. The economic importance of financial literacy: theory and evidence. J. Econ. Lit. 52 (1), 5–44.

O'Brien, R.M., 2007. A caution regarding rules of thumb for variance inflation factors. Qual. Quant. 41 (5), 673–690.

OECD. (2023). OECD International Network on Financial Education. An Overview. https://www.oecd. org/financial/education/oecd-infe-overview.pdf.

Oksanen, A., Mantere, E., Vuorinen, I., Savolainen, I., 2022. Gambling and online trading: emerging risks of real-time stock and cryptocurrency trading platforms. Public Health 205, 72–78.

Panos, G. A., Karkkainen, T., and Atkinson, A. (2020). Financial literacy and attitudes to cryptocurrencies, *Working Papers in Responsible Banking & Finance (20-002)*.

Stix, H., 2021. Ownership and purchase intention of crypto-assets: Survey results. Empirica 48 (1), 65–99.

Van Rooij, M., Lusardi, A., Alessie, R., 2011. Financial literacy and stock market participation. J. Financ. Econ. 101 (2), 449–472.

Wang, P., Bai, Z., 2025. Decoding the crypto investor profile: how financial literacy, investment experience and age shape cryptocurrency investment decisions. Humanities Soc. Sci. Commun. 12 (1), 1785.

Wu, S., 2021. Co-movement and return spillover: evidence from Bitcoin and traditional assets. SN Business & Economics 1 (10), 122.