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Cryptocurrency investment and cognitive biases in financial literacy: Evidence from the US

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Abstract

This paper examines how overconfidence in financial literacy shapes U.S. retail investors' participation in cryptocurrency markets. Using both parametric methods and causal machine-learning approaches, we find that the discrepancy between objective and subjective financial knowledge significantly increases the likelihood of crypto investment, driven primarily by self-perceived financial literacy. Causal forest analysis reveals that the effect is strongest among infrequent traders and those with lower financial well-being, suggesting that cognitive biases disproportionately impact more financially vulnerable investors. Our findings underscore the crucial role of behavioral factors in investment decisions, highlighting how misperceptions of financial knowledge can influence participation in emerging and high-risk financial markets.

Keywords: *Investment literacy; Overconfidence; Cryptocurrencies; Investment motives.*

1. Introduction

The rapid expansion of cryptocurrency markets has generated substantial academic interest in the determinants of investment in these highly volatile and complex assets. Despite sharp price fluctuations, global market capitalization reached 3.25 trillion US dollars at the end of 2024 (CoinMarketCap, 2025), underscoring persistent investor demand.

Technology-enabled innovations in investment products and services offer promising opportunities, but they also require specific knowledge of financial technologies and proper assessment of associated risks (Aristei and Gallo, 2025). Recent studies have examined the influence of financial literacy on cryptocurrency investments (Hayashi and Routh, 2025). Limited financial literacy may impair individuals' ability to assess the risks associated with crypto assets, thereby increasing their vulnerability. Conversely, higher levels of financial literacy may enable investors to evaluate cryptocurrencies more critically and consider them as a viable component of a diversified portfolio.

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Recent evidence also highlights the role of cognitive biases, particularly overconfidence, in shaping cryptocurrency ownership (Chhatwani and Parija, 2023). Individuals with higher levels of financial literacy and less biased self-assessments are less likely to hold cryptocurrencies (Carbò-Valverde et al., 2025). Additional factors have also been shown to influence participation in cryptocurrency markets. Risk perception, access to financial advice, and crypto-specific knowledge affect the behavior of crypto investors (Jones et al., 2024; Qi et al., 2025). Empirical studies have also documented strong links between cryptocurrency trading and gambling preferences, as well as the relevance of social engagement and financial motives (Delfabbro et al., 2021; Müser et al., 2024: Zhang et al., 2025).

This study contributes to the existing literature by examining how cognitive biases in financial literacy shape U.S. retail investors' participation in cryptocurrency markets. We employ both parametric and causal machine-learning approaches to gauge the impact of overconfidence on crypto investing, while controlling for financial behavior and investment motivations.

2. Data and methods

This study uses data from the 2024 Investor Survey of the National Financial Capability Study (NFCS), which targets individuals holding investments in non-retirement accounts and provides detailed information on investment behavior, knowledge, motivations, and sociodemographic characteristics. The analysis is based on a sample of 2,578 respondents with complete data.

The dependent variable is a binary indicator equal to one if the individual has invested in cryptocurrencies directly or through a fund. Descriptive evidence indicates that approximately 30% of U.S. retail investors report investment in crypto-assets, either directly or through a fund.

The main explanatory variable is *Overconfidence*, which is measured, following Piehlmaier (2022), as the residuals (normalised between 0 and 10) from a linear regression of *Subjective Investment Literacy* (i.e., self-reported knowledge about investing, ranging from 1 "very low" to 7 "very high") on a fourth-order polynomial of *Objective Investment Literacy* (i.e., latent scores from a 2PL-IRT model on the responses to eleven investment-related questions).

To assess the determinants of cryptocurrency investment and the role of overconfidence, we first consider the following probit model.

$$CI_i = \mathbb{1}[\gamma Overconfidence_i + \boldsymbol{x}_i'\boldsymbol{\beta} + \varepsilon_i > 0] \quad (1)$$

where $\boldsymbol{x}_i$ is a vector of investor-level explanatory variables, including sociodemographic characteristics, financial behavior variables, and binary indicators for investment motivations, and ε_i is a standard normal error. Using the estimates from this parametric model, we evaluate the effects of overconfidence and the other regressors on the probability of investing in cryptocurrencies by computing Average Marginal Effects (AMEs).

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To assess the robustness of the parametric results, we also estimate the effect of overconfidence using two causal machine-learning estimators: Linear Double Machine Learning (Linear DML) and the Causal Forest. Linear DML implements the double machine learning framework (Chernozhukov et al., 2018), where flexible machine learning models are used to partial out the effects of control variables in both the outcome and the treatment. The resulting coefficient measures the average marginal effect of overconfidence under the minimal functional form assumptions. The causal forest estimator (Athey et al., 2019) extends random-forest methods to estimate heterogeneous treatment effects. In this framework, the marginal effect of overconfidence is allowed to vary across individuals, producing observation-specific treatment effects whose average provides an overall estimate comparable to the parametric AME.

3. Empirical results

Table 1 reports the AMEs on the probability of investing in cryptocurrencies, estimated from three specifications: the first includes only demographic characteristics, the second incorporates investment behavior variables, and the third adds investment motive indicators.

The overconfidence variable, measured as the mismatch between objective and subjective financial knowledge, has a positive and statistically significant effect on the likelihood of investing in crypto-assets. Consistent with Santiago Carbó-Valverde et al. (2025), this suggests that overestimating one's financial knowledge increases engagement in high-risk investments. A one-unit increase in overconfidence raises the probability of crypto investment by 1.62, 1.86, and 1.03 percentage points across the three specifications, respectively, clearly indicating that overconfidence is a key determinant of cryptocurrency participation even when investors' behavior and motivations are taken into account.

Table 1 – Cryptocurrency investment and overconfidence: parametric estimates

	(1)	(2)	(3)
Model:	**Probit**	**Probit**	**Probit**
Overconfidence	0.0162*** (0.0038)	0.0186*** (0.0039)	0.0103*** (0.0040)
Female	-0.0903*** (0.0151)	-0.0788*** (0.0160)	-0.0608*** (0.0167)
Non-white	0.0777*** (0.0229)	0.0522** (0.0209)	0.0391** (0.0199)
Age 35-54	-0.1436*** (0.0383)	-0.0891*** (0.0345)	-0.0749** (0.0346)
Age 55 or above	-0.3408*** (0.0375)	-0.2278*** (0.0362)	-0.1875*** (0.0364)
College graduate or more	-0.0628*** (0.0151)	-0.0465*** (0.0160)	-0.0509*** (0.0162)
Income $50k-$100k	0.0025 (0.0225)	0.0308 (0.0226)	0.0397* (0.0220)
Income $100k+	0.0126 (0.0218)	0.0498** (0.0238)	0.0586** (0.0234)
Employee	0.0083 (0.0284)	0.0336 (0.0299)	0.0087 (0.0306)
Self-employed	0.0134 (0.0354)	0.0279 (0.0394)	0.0293 (0.0389)
Retired	-0.0487 (0.0303)	-0.0056 (0.0325)	-0.0173 (0.0335)
Financial well-being		-0.0270*** (0.0071)	-0.0199*** (0.0070)

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Portfolio value $50k+		-0.0442** (0.0186)	-0.0375** (0.0183)
Invest since 10 years ago		-0.0583*** (0.0174)	-0.0320* (0.0170)
Frequent trading		0.1238*** (0.0237)	0.1162*** (0.0246)
Professional advice		-0.0627*** (0.0159)	-0.0717*** (0.0159)
Risk averse		-0.1240*** (0.0225)	-0.1115*** (0.0220)
Crypto not/slightly risky		0.2566*** (0.0440)	0.2570*** (0.0468)
Entertainment			0.1226*** (0.0223)
Peer pressure			0.0408* (0.0222)
Short-term returns			0.0136 (0.0181)
McFadden pseudo R2	0.1838	0.2589	0.3190
Correctly classified	81.23%	82.05%	83.25%
N	2,578	2,418	2,280

***Notes**: The Table reports average marginal effects on the probability of having invested in cryptocurrencies. The dependent variable is a binary indicator that equals one if the respondent has invested in cryptocurrencies directly or through a fund. All the models include Federal State fixed effects. Robust standard errors, clustered by Federal State and age group, are reported in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.*

With respect to the other covariates, the results reveal a gender gap in crypto-asset participation, with women being significantly less likely to invest in crypto assets. Moreover, investors under 35 years old, individuals with lower levels of education, and non-white investors are more likely to invest in cryptocurrencies. These results are robust across all three specifications considered. Furthermore, individuals with higher levels of financial well-being, larger financial portfolio values, and greater risk aversion display a lower propensity to invest in cryptocurrencies. By contrast, variables capturing investment motivations, such as entertainment and peer pressure, exert a positive and statistically significant effect on the probability of investing in crypto assets, showing how behavioral and social factors can drive investment decisions. Specifically, investors who perceive trading as a gambling-like activity are significantly more likely to invest in cryptocurrencies, with a probability increase of 12.26 percentage points.

To further assess the role of overconfidence in cryptocurrency investment, we conduct a robustness check by replacing the overconfidence variable with separate measures of objective and subjective financial literacy, following the approach of Parker and Stone (2014). The results, reported in Table 2, suggest that the relationship between overconfidence and crypto-asset investment is primarily driven by subjective financial literacy. In particular, subjective financial knowledge is positively and significantly associated with the likelihood of investing in crypto assets across all specifications, while objective financial literacy is not statistically significant. These findings confirm that perceived financial knowledge, rather than actual financial knowledge, plays a key role in crypto-asset investment decisions.

Table 2 – Cryptocurrency investment and investment literacy: parametric estimates

	(1)	(2)	(3)
Model:	**Probit**	**Probit**	**Probit**

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Objective investment literacy	0.0018 (0.0036)	-0.0014 (0.0036)	0.0017 (0.0037)
Subjective investment literacy	0.0230*** (0.0051)	0.0262*** (0.0053)	0.0151*** (0.0054)
McFadden pseudo R2	0.1852	0.2593	0.2801
Correctly classified	81.07%	81.93%	83.25%
N	2,578	2,418	2,280

Notes: *The Table reports average marginal effects on the probability of having invested in cryptocurrencies. The dependent variable is a binary indicator that equals one if the respondent has invested in cryptocurrencies directly or through a fund. All the models include the same covariates as in Table 1, and Federal State fixed effects. Robust standard errors, clustered by Federal State and age group, are reported in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.*

Table 3 presents results from linear DML and causal forest models.[1] Across the three specifications, both machine-learning estimators produce treatment effect estimates that are very similar to parametric marginal effects (panel A). In the specification controlling only for demographics, the Linear DML and causal forest estimates are approximately 0.0186, slightly larger but close to the probit AME. When financial controls are included, the estimated effect ranges between 0.0204 and 0.0217. After controlling for investment motives, the effect remains positive and statistically significant, ranging from 0.0143 to 0.0168. Moreover, goodness-of-fit indicators for both the machine-learning models show a sharp increase as additional covariates are added to the baseline specification. Overall, the similarity between parametric and machine learning estimates indicates that the positive effect of overconfidence on cryptocurrency investment is robust to flexible modelling of confounding factors.

Table 3 – Cryptocurrency investment and overconfidence: causal machine-learning estimates

Model:	**(1)** **Linear DML**	**(2)** **Causal forest**
Panel A: Estimated marginal effect of overconfidence		
Demographics	0.0186*** (0.0042)	0.0186*** (0.0041)
+Financial controls	0.0217*** (0.0048)	0.0204*** (0.0043)
+Financial controls & investment motives	0.0168*** (0.0051)	0.0143*** (0.0044)
Panel B: Goodness-of-fit indicators		
	Outcome R2	**Treatment R2**
Demographics	0.1873	0.0608
+Financial controls	0.2874	0.1527
+Financial controls & investment motives	0.2994	0.1904

Notes: *The Table reports average marginal effects of overconfidence on cryptocurrency investment. The dependent variable is a binary indicator that equals one if the respondent has invested in cryptocurrencies directly or through a fund. All the models include the same covariates as in Table 1, and Federal State fixed effects. Standard errors are*

[1] Categorical covariates and State fixed effects are included in the machine learning nuisance models by using one-hot encoding with a dropped baseline category. To reduce instability resulting from sparse dummy combinations, nuisance parameters in both models are estimated by random forest using cross-fitting with a minimum leaf size of 20, while the causal forest imposes a minimal leaf size of 15.

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*reported in parentheses. The machine-learning R2 statistics refer to the predictive performance of the nuisance outcome and treatment models used by the Linear DML and causal forest estimators. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.*

The causal forest approach allows heterogeneous treatment effects. This enables us to assess which covariates are most relevant in explaining heterogeneity in the estimated causal effects. Figure 1 indicates that heterogeneity is primarily driven by trading frequency, financial well-being, age, and investment motives related to peer pressure and entertainment. These findings suggest that cryptocurrency participation is shaped by the interaction between cognitive biases, financial conditions, and investors' behavior and motivations.

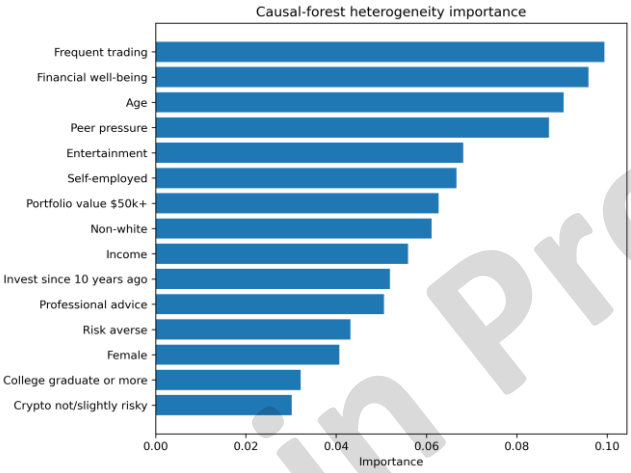


Figure 1 – Causal forest variable importance for treatment effect heterogeneity

The partial dependence curves in Figure 2 show that the effect of overconfidence is stronger among investors who trade infrequently and those with lower financial well-being. Cognitive biases in perceived financial literacy may be especially problematic for financially vulnerable investors, increasing their propensity to invest in highly volatile and technologically complex financial instruments and exposing them to excessive risk-taking.

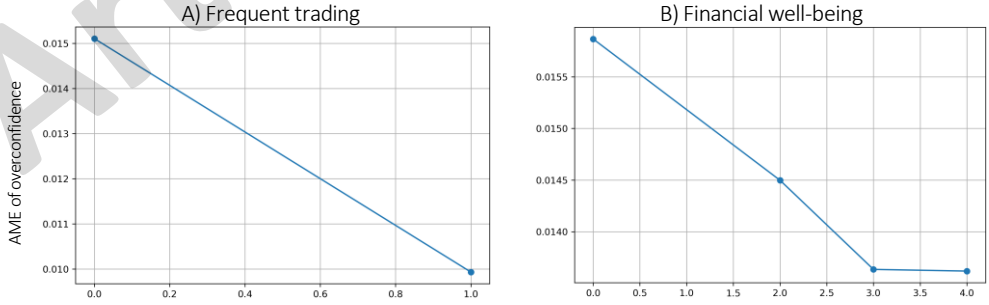


Figure 2 – Average marginal effect of overconfidence by trading frequency and financial well-being

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Table 4 evaluates the robustness of the estimates by replacing State fixed effects with broader regional fixed effects based on the four U.S. Census regions (i.e, Northeast, Midwest, South, and West). This substantially reduces the dimensionality of the categorical controls while preserving geographic heterogeneity. The estimated average marginal effects remain highly stable across Probit, Linear DML, and Causal Forest models, suggesting that the results are not driven by the high dimensionality introduced by State fixed effects in the baseline models.

We further assess the robustness of causal forest estimates by allowing the minimum leaf size to vary between 10 to 40. The results (available upon request) indicate that the estimated AMEs of overconfidence remain unchanged across specifications, with the dispersion of individual treatment effects reducing as the minimum leaf size increases. This suggests that the results are not driven by unstable subgroup partitions or overfitting in sparse cells.

Table 4 – Robustness: replacing State fixed effects with Census Region fixed effects

Model:	(1) Probit	(2) Linear DML	(3) Causal forest
Demographics	0.0171*** (0.0037)	0.0173*** (0.0040)	0.0179*** (0.0042)
+Financial controls	0.0192*** (0.0038)	0.0197*** (0.0043)	0.0198*** (0.0033)
+Fin. controls & investment motives	0.0108*** (0.0038)	0.0144*** (0.0045)	0.0135*** (0.0043)

Notes: *The Table reports average marginal effects of overconfidence on cryptocurrency investment. The dependent variable is a binary indicator that equals one if the respondent has invested in cryptocurrencies directly or through a fund. All the models include the same covariates as in Table 1, and Census Region fixed effects. Standard errors are reported in parentheses. ***, ** and * denote significance at the 1, 5 and 10% levels, respectively.*

4. Conclusions

This paper examines the role of overconfidence in individuals' participation in cryptocurrency markets. The results show that overconfidence, measured as the gap between subjective and objective financial knowledge, significantly increases the probability of investing in crypto assets. This effect is robust across alternative model specifications and after controlling for demographic characteristics, financial conditions, and investment motivations. Additional analysis shows that this relationship is mainly driven by subjective financial literacy: individuals who perceive themselves as financially knowledgeable are more likely to invest in cryptocurrencies, while objective financial knowledge is not statistically significant. Estimates obtained using machine-learning methods confirm the robustness of these results. Moreover, the causal forest analysis reveals substantial heterogeneity in treatment effects, particularly across trading frequency, financial well-being, age, and behavioral motivations. The effect of overconfidence is stronger among infrequent traders and individuals with lower financial well-being, suggesting that cognitive biases may disproportionately affect more financially vulnerable investors. These findings highlight the need for educational initiatives to reduce cognitive bias in perceived financial literacy and foster responsible participation in cryptocurrency markets, especially among vulnerable and less experienced investors.

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