From Crypto to NFTs: Identifying the New Wave of Digital Investors*

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Abstract

The objective of this paper is to explore whether NFT investors represent a distinct cohort within the broader crypto investment sphere. Employing data from a public survey with global outreach, we first find that NFT owners are younger and possess, on average, a lower educational level than the general crypto population but a higher cryptocurrency knowledge. Second, there are no significant gender differences among NFT investors and non-NFT investors, but those working in the crypto sphere are more likely to invest in NFTs. Additionally, individuals involved in yield farming or using crypto derivatives are more likely to own NFTs. Finally, we show that individuals with more concerns about the potential misuse of cryptocurrency for illicit activities are less likely to engage in the ownership of NFTs.

JEL Classification: D14 D91 E42 G11 G12 G28 O33

Keywords: Non-Fungible Tokens, cryptocurrencies, investor profile, household finance

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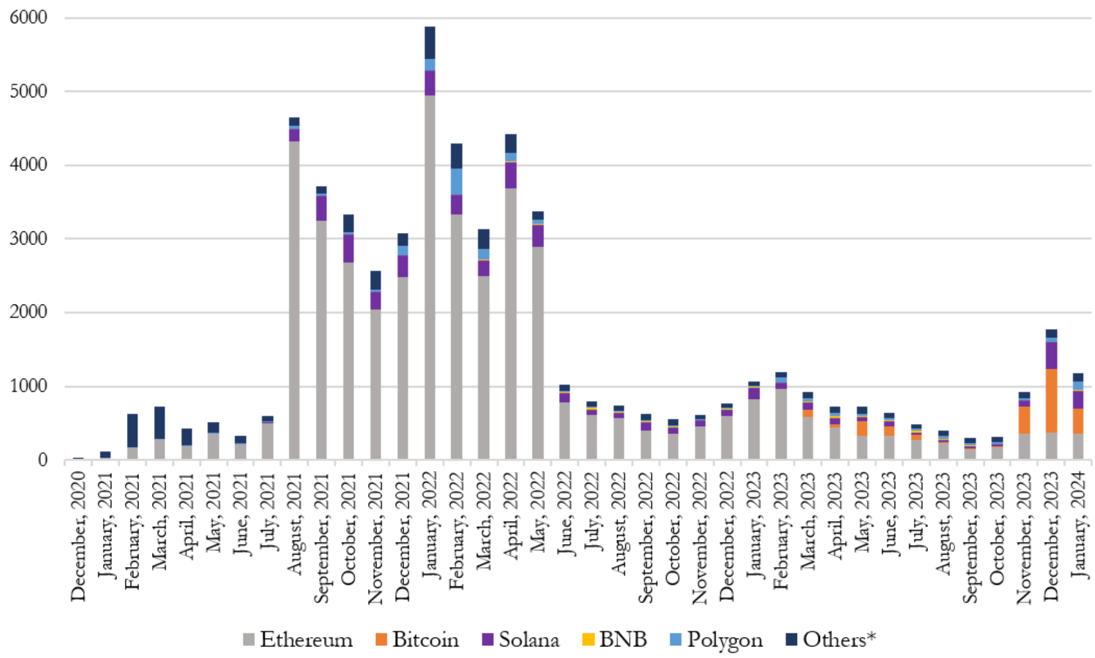
*We are grateful to the editor and the anonymous referees for their useful comments and suggestions. All authors have contributed equally to this paper.

1 Introduction

Non-fungible tokens (NFTs) are unique digital items stored on a blockchain. Unlike cryptocurrencies, which are fungible (each unit is identical in value and function), NFTs represent singular, indivisible digital items that cannot be exchanged on a one-to-one basis. Originated as a token standard within the Ethereum blockchain, NFTs constitute a novel asset category representing ownership of unique items; that is, each NFT possesses distinct digital characteristics, enabling their individualized assessment and identification (Borri et al., 2022).

NFTs have driven innovation in digital ownership, enabling the tokenization of diverse items such as artwork (Vasan et al., 2022), collectibles (Serada, 2024), and even real estate (Serrano, 2022). Their uniqueness[1] and indivisibility ensure a clear distinction between different items, enhancing their value as scarce digital assets. NFTs serve to authenticate and verify ownership within the blockchain ecosystem. However, this does not extend to rights to reproduce or distribute the original work. The relevance of NFTs lies in their ability to authenticate and verify ownership of digital items within the blockchain ecosystem.

Figure 1: NFT sales volume by chain (in millions of USD).



Source: CryptoSlam! **Others* include the sum of NFT market sales in the following blockchains: Mythos, Immutable, Avalanche, Arbitrum, Cardano, Flow, Tezos, WAX and Panini.

[1]NFTs exclusivity allows them only one official owner at a given time.

The NFT market[2] experienced a remarkable growth from 2021 into the second quarter of 2022, with most sales occurring on the Ethereum blockchain (see Figure 1). This notable expansion has significantly impacted the market for decentralized applications (dApps), yielding staggering returns (Ali et al., 2023) and capturing widespread global attention. Their even faster decline in traded volumes during the 2022-2023 crypto winter intensified scrutiny, generating renewed curiosity about the resilience and long-term viability of this market.

Considering the landscape of the NFT ecosystem and its relatively nascent nature, there is a lack of understanding regarding the profile of retail investors actively involved in the NFT market, including their demographic characteristics, investing behavior, trust levels, attitudes towards crypto and society and familiarity with conventional financial and crypto education. As Borri et al. (2022) and Horky et al. (2022) have shown, NFTs tend to exhibit different behavior compared to cryptocurrencies, positioning them as a new and alternative financial asset. Therefore, the objective of this paper is to explore whether the investors engaged in NFTs represent an entirely unique cohort within the broader crypto investment sphere.

In particular, we aim at examining whether NFT owners[3] differ from non-NFT users in their sociodemographic and financial profiles. Moreover, the paper seeks to understand whether the primary reason to invest in crypto may be different from NFT owners versus non-NFT owners—in other words, if they have a more speculative nature. We also analyze whether NFT users have different attitudes towards some relevant aspect in the society, such as scams, taxes and trust in the government.

We employ the State of Crypto Survey, a micro-level dataset constructed over the period October-December 2022 to gather data about cryptocurrency investors worldwide. Using a variety of econometric specifications, we first find that NFT owners, on average, possess a lower educational level compared to the general crypto population that do not own NFTs. At the same time, younger crypto investors

[2]The history of NFTs dates back to 2014 when the first NFT, Quantum, was created by digital artist Kevin McCoy on May 3. Quantum is a digital image featuring a pixelated, pulsating octagon, minted on the Namecoin blockchain. While it was not initially sold for a significant sum, it gained attention in June 2021 when it was auctioned for $1.47 million at Sotheby's (see https://nftnow.com/art/quantum-the-first-piece-of-nft-art-ever-created/). Nevertheless, the most expensive NFT sale to date is The Merge by the pseudonymous artist Pak, which was sold for $91.8 million in December 2021. The second most expensive NFT sale is Beeple's Everydays: The First 5000 Days, a digital collage consisting of 5,000 daily images created over 13 years. It was sold for a record-breaking $69.3 million at Christie's auction in March 2021, bought by the investor Metakovan (Vignesh Sundaresan) (see https://www.stadioplus.com/post/most-expensive-nft-art.

[3]NFT owners/users/investors are used indistinctly along this paper.

are more prone to invest in NFTs. Third, a higher cryptocurrency knowledge—in particular, about NFTs—is associated with a higher likelihood of owning NFTs, suggesting, not surprisingly, that individuals with a deeper understanding of the NFT landscape are more inclined to engage with and invest in NFT assets. Fourth, compared to the non-NFT owners population, NFT investors show no differences in their gender. We do, however, find that Asians tend to invest more in NFTs than the non-Asian population.[4] Also, working in the crypto sphere increases the probability of investing in NFTs. This finding suggests that individuals immersed in the crypto sphere, through their professional engagement, are not only exposed to a diverse range of crypto assets but also may perceive NFTs as a valuable investment opportunity.

Our second set of results regards the broader investing attitudes of cryptocurrency investors. Our research reveals that individuals engaged in yield farming, a practice involving staking or lending cryptocurrencies to earn extra tokens, are more likely to own NFTs. Yield farming constitutes a fundamental component of decentralized finance, which encompasses financial systems that operate without traditional financial intermediaries (i.e., banks). Notably, yield farming often involves the use of leverage, wherein participants borrow against staked assets to amplify returns. While this practice has the potential to enhance gains, it also introduces significant financial risks and has been closely associated with speculative trading strategies prevalent within the cryptocurrency ecosystem. Prior literature has explored the mechanisms and implications of yield farming and its role within decentralized finance. For example, Auer et al. (2024) stress the use of leverage in yield farming and its broader implications for market dynamics. Heimbach and Huang (2024) analyze the relationship between leveraged positions and market volatility. In particular, they examine leverage within decentralized finance lending platforms, focusing on how borrowers' leverage levels influence their choice of collateral, particularly as they approach liquidation thresholds. Their study reveals that borrowers with higher leverage are more inclined to select volatile collateral when their debt positions are nearing liquidation. Similarly, Saengchote (2023) provides a comprehensive overview of yield farming's integration within the decentralized finance ecosystem, emphasizing its association with speculative and investment behaviors. As it seems that yield farming frequently entails speculative strategies and a tolerance for risk, it may align closely with the motivations behind

[4] Ji et al. (2015) have underscored that some cultural groups may be more susceptible to gambling. Since gambling has been linked to the ownership of digital assets, including NFTs (Lopez-Gonzalez and Petrotta, 2023), it may be worth it to explore more this connection in future research papers.

NFT investments. Yield farmers' tendency to own NFTs may reflect a shared inclination toward high-risk, high-reward financial practices within the crypto ecosystem.

In a similar vein, our results highlight a positive association between using crypto derivatives and the probability of possessing NFTs, suggesting that individuals actively involved in cryptocurrency derivative markets are more likely to be engaged in NFT ownership. Interestingly, higher percentage of their total investment in Bitcoin is negatively correlated with owning NFTs. In other words, it seems that cryptocurrency owners that tend to invest more in BTC (relatively to their total investments) are less likely to invest in NFTs. One may think that this can happen because Bitcoin investors, i.e., traditional crypto investors, are more comfortable with the established nature of BTC. On the contrary, we observe that NFT ownership is correlated with ownership of altcoins such as BNB and MATIC.

Our last set of results focuses on NFT investors' attitudes towards scams, governmental issues and the purpose of investing in cryptocurrencies. These issues are deeply embedded in the broader ideological and practical narratives that have shaped the cryptocurrency ecosystem since its inception. Cryptocurrencies, epitomized by Bitcoin, were founded on principles of decentralization, financial autonomy, and skepticism toward centralized institutions. Satoshi Nakamoto's foundational white paper outlined a vision for a "peer-to-peer electronic cash system" designed to function without trusted intermediaries (Nakamoto, 2008). This ethos remains a cornerstone of the cryptocurrency narrative, influencing the behaviors and attitudes of its participants. Survey questions addressing "trust in government" and concerns about "mass control" reflect these enduring themes, which continue to resonate with crypto investors. In addition, we have incorporated into our analysis the taxation dimension. The survey's inclusion of questions related to taxation highlights a critical practical dimension of cryptocurrency investment. Crypto-assets, including NFTs, have frequently been associated with complex tax challenges.[5] The relevance of tax considerations has been therefore underscored in recent academic studies and media analyses. Nguyen (2022) explains that the taxation of NFTs remains relatively unclear compared to the more established

[5] Emphasizing the importance of tax compliance in the crypto ecosystem, Agyemang (2022) highlights a landmark case where HM Revenue & Customs (HMRC) in the UK seized NFTs and other crypto assets worth £5,000 as part of an investigation into a £1.4 million VAT fraud. This action represents the first NFT seizure by a UK law enforcement agency and serves as a warning to those attempting to evade taxes using crypto assets.

framework for cryptocurrencies in the U.S. The lack of clarity forces taxpayers to rely on the cryptocurrency tax framework, which does not fully address the unique aspects of NFTs. Some have sought innovative ways to manage their NFT-related tax obligations. For instance, as NFT values have plummeted amidst the broader cryptocurrency downturn in 2022, some services have emerged to help collectors monetize losses. These services purchase "worthless" NFTs for minimal amounts, providing sellers with official receipts that enable them to claim significant tax write-offs (Helmore, 2022). Despite these complexities, our analysis reveals that the opinions regarding taxation do not differ significantly between NFT and non-NFT owners. Tax-related considerations, while salient in the broader cryptocurrency discourse, may not be a distinguishing factor in NFT ownership. Moreover, we show that individuals with heightened concerns about the potential misuse of cryptocurrencies for illicit activities are less likely to own NFTs. Our result aligns with the broader narrative of risk aversion among certain segments of crypto investors, particularly those wary of the regulatory and reputational implications associated with NFTs and other cryptoassets.

Our study on the profile of NFT investors offers insights across multidisciplinary domains in economics, finance, psychology and sociology. First, it expands the literature related to the study of this new asset class. Borri et al. (2022) explored the market dynamics, returns, and investor behaviors within the NFT market.[6] They find that NFTs tend to show distinct behaviors compared to both established asset classes and cryptocurrencies, which may indicate the presence of unique driving forces specific to the NFT market. From a pricing perspective, Horky et al. (2022) reinforce the previous point, underscoring that that NFTs are different from cryptocurrencies and can be perceived as a complete new and alternative financial asset.

Second, our research contributes to the academic research literature attempting to characterize the socioeconomic and psychological features of crypto users. Most of these studies have primarily focus on Bitcoin users that are located in advanced economies. For instance, drawing on a survey of Canadian individuals, Henry et al. (2018) find that being male and having a higher level of education raise the likelihood of Bitcoin awareness. In Austria, Stix (2019) stresses that crypto owners tend to be younger and more open to accepting financial risk. In Japan, Fujiki (2020)

[6]Some papers have explored the market dynamics and pricing of particular NFT segments. For instance, Kong and Lin (2021) focus on one of the most representative NFT collections, the CryptoPunks. Dowling (2022) and Goldberg et al. (2021) focus on the price of virtual land in Decentraland.

discovers that crypto holders are more likely to be male, young, have a high pre-tax income, and possess a high level of financial literacy. In a similar vein, using a United States sample, Auer and Tercero-Lucas (2022) show that cryptocurrency investors tend to be male[7], educated, young and have a higher experience using digital finance. Also for the US, Aiello et al. (2023) observe that early adopters of cryptocurrency generally exhibit higher income and spending levels, as well as greater financial sophistication. In addition, crypto investors generally have higher incomes and encounter fewer financial constraints compared to households that do not participate in crypto markets. Zhao and Zhang (2021) find that people with a higher financial literacy level and that have experience investing in traditional markets are more likely to invest in cryptocurrencies. In emerging markets, trends are similar. Colombo and Yarovaya (2024) show that Brazilian cryptocurrency investors are mostly young and male and exhibit higher risk tolerance and self-perceived investment expertise. Regarding psychological features, Kim et al. (2020) stress that psychological states, unique investment patters and personality are distinctive in Bitcoin investors. Oksanen et al. (2022) also documents that crypto users report higher both psychological distress, perceived stress and a feeling of loneliness.

Third, this paper contributes to the literature that has focused on understanding the attitudes of crypto users and investors in the crypto scene. Several papers have tried to analyze the relevance of news in cryptocurrency investors' behavior (Flori, 2019; Domingo et al., 2020), the presence of herding behavior in the crypto market (Stavroyiannis and Babalos, 2019) and the importance of investor sentiment (Nie et al., 2020; Guégan and Renault, 2021). Our results pointing that NFT owners are more inclined toward yield farming may be attributed to its growing popularity in some online computer games (Delfabbro et al., 2022; De Jesus et al., 2022). The relationship between investing in cryptocurrencies and gambling and gaming is also well-documented in the literature. Oksanen et al. (2022) find that crypto traders spend substantially more hours on gampling and gaming than non-crypto users. Similarly, Kim et al. (2020) points out that Bitcoin investors tend to display higher gambling tendencies. Without confining the analysis exclusively to Bitcoin investors, Aiello et al. (2023) find that they are significantly more likely to engage in gambling behavior. However, we find that those crypto users who use crypto derivatives also

[7]The gender gap in cryptocurrency ownership is well-documented in the literature. Using a sample of Spanish individuals, Alonso et al. (2023) have identified that barriers to female acceptance of cryptocurrencies include limited experience in traditional asset investment, a general lack of knowledge about cryptocurrencies, and concerns about the security and perceived risks associated with crypto transactions.

have an interest in NFTs.[8] In addition, the cryptocurrency literature has identified that crypto investors tend to hold risky portfolios, investing in assets with high media sentiment (Hackethal et al., 2022).

Our findings underscore several policy considerations. Firstly, the distinctive profile of NFT investors—characterized by a lower average educational level compared to the non-NFT and broader crypto population, heightened crypto knowledge, skepticism toward scams in the crypto world, and a greater propensity for yield farming and derivatives activities—highlights the emergence of a unique market segment that warrants dedicated regulatory attention. This subgroup of NFT investors not only presents new challenges but also offers opportunities for tailored regulatory frameworks that acknowledge the specific dynamics of the NFT market.

Secondly, addressing the growing data gaps in the cryptocurrency industry becomes imperative. As NFTs gain prominence within the broader crypto landscape, understanding their unique market dynamics and assessing potential risks demand comprehensive and up-to-date data. Enhancing the systematic collection and publication of data related to NFT transactions (Nadini et al., 2021), ownership (Vasan et al., 2022), and market trends (Alizadeh et al., 2023) will contribute to a more robust regulatory oversight, allowing authorities to make informed decisions in a rapidly evolving space.

Lastly, recognizing the potential interlinkages between NFT platforms and traditional financial institutions is crucial. As the demand for NFTs grows, their integration with the established financial nodes may increase. Understanding and mitigating associated risks should guide regulatory efforts. A proactive, forward-looking regulatory approach is essential to foster a secure and sustainable environment as NFTs become more interconnected with the broader financial system, in particular in a world where the widespread adoption of cryptocurrencies has transcended national borders, becoming a global phenomenon that spans economies with varying levels of economic development and financial awareness.

The remainder of this paper is structured as follows. Section 2 presents the data collection process, the main data employed in this study and outlines the empirical strategy used to identify the effects of interest. Section 3 provides an overview of the

[8] However, Horky et al. (2022) show that NFTs cannot be seen as a pure derivative of cryptocurrencies but an alternative financial asset.

main results and presents robustness checks. Section 4 concludes.

2 Data and methodology

2.1 Data Collection

The data employed in this study belong to the State of Crypto Survey.[9] This survey was launched over the period Oct-Dec 2022[10] in multiple social media channels, especially X (formerly known as Twitter), one of the most used social media of the crypto space.[11] To bolster the inclusion of all crypto communities world wide, the survey was translated in 29 languages.

Data were collected through the survey from 3,752 respondents, 2000 of whom completed it (our preregistered target). Participants joined from across the globe, with self-reported locations spanning over 170 countries. The most represented countries were Turkey (13.3% of the data), China (12.3%), Indonesia (12.9%), and the USA (5.4%).

The survey gathered information about several variables of crypto and non-crypto investors, including demographic and socioeconomic variables (gender, education, age, race, employment situation), financial literacy, risk profiles and investing profiles. Additionally, the survey explored issues such as inequality, trust in the government, and the perceived purpose of crypto. The survey was implemented in nodeGame (Balietti, 2017), was preregistered on AsPredicted.org[12], received IRB clearance

[9]The State of Crypto Survey is an interdisciplinary research initiative formed in 2021 by academic scholars from diverse backgrounds, aimed at exploring the societal impact of cryptocurrency as a cultural, social, technical, and economic system. State of crypto researchers have no affiliations to crypto projects, ensuring complete independence and transparency. State of Crypto prioritizes inclusivity, with surveys translated in multiple languages and all findings made publicly accessible, also as popular science reads. All State of Crypto projects follow a strict non-deception policy, undergo an ethics committee approval, and are fully GDPR compliant, ensuring confidential data handling and secure storage. See https://stateofcrypto.net for additional information about the survey.

[10]The reader should be aware that during the period from October to December 2022, the cryptocurrency market experienced notable volatility, especially because of the collapse of the FTX exchange in November. Additionally, the economic environment was characterized by rising interest rates and inflation.

[11]Several papers have remarked the relevance of Twitter in the crypto sphere. For instance, Kraaijeveld and De Smedt (2020) find that Twitter sentiment helps to predict the returns of particular tokens such as BTC, BCH, and LTC. In a similar vein, Zhang and Zhang (2022) show that not only crypto prices react in a positive way to Twitter sentiments but also crypto trading volume reacts in a positive manner to the absolute value of the Twitter sentiments.

[12]See https://aspredicted.org/Y31_5RB and Appendix D for further information about the preregistration.

(EK Mannheim 50/2021), and was checked for GDPR compliance. For additional information about how the data were treated, see Appendix B.

2.2 Main data

The aim of this study is to explore whether NFT investors represent an entirely unique cohort within the broader crypto investment sphere. Hence, we are restricting our sample to merely cryptocurrency owners. NFT ownership is our main variable of interest and it captures whether an individual owns (or has owned) at least one NFT. The survey also captures information on the various types of NFTs owned by respondents. In the primary regression sample (Table 6, N = 1086), NFT ownership was reported by 597 individuals (respondents were allowed to select multiple NFT categories). The distribution of ownership includes Art NFTs (342), Domains (242), Utility NFTs (209), Collectibles (336), Virtual Land (118), and other categories (12).

To explain the features of NFT investors, we are using data related to three main categories of explanatory variables: i) socio-economic and risk profile variables, ii) investing profile variables and iii) variables related to attitudes towards crypto and society. Table 1 summarizes and provides an overview of the explanatory variables that have been included in the empirical analysis as potential features of NFT investors. Appendix A provides additional information about each of these variables.

Socio-economic and risk profile variables. These are variables that capture sociodemographic and socioeconomic indicators of cryptocurrency investors in our survey including the educational level, their age range[13], gender, their level of crypto literacy[14], financial literacy, their working status, if they work in the crypto sphere, and race.[15] This category also includes risk profile variables such as risk seeking and their social value orientation (SVO).

Investing profile. These are variables that capture the behavior of cryptocurrency owners as investors, such as when they were first interested in crypto, percentage of their portfolio invested in crypto, percentage of their overall crypto portfolio in Bitcoin, number of cryptocurrencies currently owned, whether

[13] Age is divided into seventeen categories (see Appendix A for additional details).

[14] We construct three different crypto indexes: i) "Know crypto general" that assess the knowledge about crypto in five questions (maximum achievable score = 5), ii) "Know crypto NFT" that assess the general knowledge about NFTs in one question, and iii) "Know crypto" that combines both previous variables (maximum score achievable of 6).

[15] Race was divided in twelve categories (see Appendix A for additional details).

Table 1: Potential features of NFT investors

Variable	Code	Definition
Socio-economic and risk profile		
Variable	Code	Definition
Education	*Edu*	Maximum educational level achieved.
Place of residence	*Country*	Country in which the respondent currently resides.
Race	*Race*	Race to which one classifies herself to.
Age	*Age*	Age range at the time of answering the survey.
Gender	*Gender*	Gender one identifies herself to (male, female, non-binary, other).
Work status	*Is working*	Working status of the respondent.
Working in crypto	*Works in crypto*	If the respondent works in the crypto sector or not
Cryptocurrency literacy	*Know crypto general*	Index that measures the level of crypto literacy.
NFT knowledge	*Know crypto NFT*	Index that measures the level of NFT literacy.
Financial literacy	*Know finance*	Index that measures the level of financial literacy.
Risk seeking	*Risk seeking*	Whether a participant chose to open more than 50 boxes in the Bomb risk elicitation task (Crosetto and Filippin, 2013).
SVO	*SVO*	Social Value Orientation computed as in Murphy et al. (2011).
Investing profile		
Variable	Code	Definition
Wealth invested in cryptocurrencies	*Wealth inv. Z*	Percentage of the overall investment portfolio in crypto.
Interest in cryptocurrencies	*When interested*	When the respondent got interested in crypto for the first time.
Bitcoin share	*BTC share*	Percentage of overall crypto portfolio in Bitcoin.
Investment in derivatives	*Derivatives*	Whether the person invests in derivatives or not.
Farming	*Farming*	Whether the person engages in farming activities or not.
Leverage	*Leverage*	Opinion on whether the respondent has ever used leverage (borrowed money) to fund your cryptocurrency investments.
Stocks and bonds	*Stocks*	Whether the person is a bond or stock investor.
Overconfidence	*Overconfidence*	Percentage of investors a respondent thinks performed better than her in the previous year (2021).
Number of different cryptocurrencies held	*No. cryptos held*	Number of different cryptocurrencies held by an investor.
Attitudes towards crypto and society		
Variable	Code	Definition
Taxes	*Taxes*	Opinion on whether all cryptocurrency gains should be taxed.
Scams	*Scams*	Opinion on whether cryptocurrencies facilitate money laundering and scams more than cash or other means of payment.
Trust in government	*Trust in gov.*	Opinion on whether how much of the time the respondent thinks she can trust the government in the country where she lives to do what is right.
Mass control	*Mass control*	Opinion on whether individuals are worried about cryptocurrencies been used as an instrument of mass control.
Risk staking	*Risk staking*	Opinion about whether governance protocols based on staking coins may allow the richest individuals and groups to buy the votes (stakes) they need to implement the governance they want.
Original purpose of crypto	*Purpose-Satoshi*	Opinion on how respondents feel about the evolution of crypto.
Purpose of crypto	*Purpose-you*	Respondents' opinion regarding the main purpose of cryptocurrencies.
Reasons to invest in crypto	*Supports crypto*	Primary reason to invest in crypto.
Cryptocurrencies for speculation	*Cryptocurr. for spec.*	From previous "Purpose-you", it takes a value of 1 if the respondent considers that crypto is a means of speculation and 0 otherwise.
Satoshi not Betrayed	*Satoshi not Betrayed*	From previous "Original purpose of crypto", it takes a value of 1 if the respondent considers that crypto has betrayed the original purpose envisioned by the creator of Bitcoin, Satoshi Nakamoto, 0 otherwise.

Note: additional details are provided in Appendix A.

they are a bond or stock investor, if they have ever used options or other crypto derivatives, if they have ever used leverage to fund cryptocurrency investments, and if they have ever used crypto yield farming. Finally, we included a variable to capture overconfidence, i.e., what percentage of investors a respondent thinks performed better than her in the previous year to the survey.

Attitudes. These variables capture the attitudes of crypto users towards taxes (if they think that all cryptocurrency gains should be taxed), scams (if they think that cryptocurrencies facilitate money laundering and scams more than cash or other means of payment), their government (how much of the time they think they can trust in their government), staking (if they are worried that governance protocols based on staking coins will allow the richest individuals and groups to buy the votes (stakes) they need to implement the governance they want) and mass-control (if they are worried about cryptocurrencies being used as an instrument of mass control). Finally, we also include in this category variables that capture the opinion of crypto users regarding how they feel about the evolution of crypto and the main purpose of cryptocurrencies (e.g., "Supports crypto", "purpose-Satoshi" and "purpose-you").

Table 2 provides summary statistics for the variables included in the benchmark specification.[16] In our main specification, 55% of crypto users own or have owned at least one NFT. From our respondents, the average age is 34 years old, 92% are male, 40% classify themselves as Asian, and around 38% work in the crypto sector.

2.3 Methodology

In order to corroborate or disprove the hypothesis that NFT investors have particular features within the overall crypto investor crowd, we employ a logistic regression model.

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

where $\Lambda(.)$ represents the standard normal logistic distribution function. $Y_{i,t}$ is a categorical variable that takes the value 1 if individual i owns or owned at least one NFT, and 0 otherwise. S_i is a vector of socio-economic variables at individual level, I_i is a vector of investing profile variables at individual level, and $A_{i,t}$ is a vector of attitudes at individual level. Finally, standard errors are clustered by continent.

The logistic regression model is estimated through maximum likelihood. In the logit model, we assume the error term follows a standard logistic distribution, logistic

[16] Table A3, in the Appendix, presents the main correlations among the variables employed.

Table 2: Summary statistics

	Mean	SD	Min	Max	Median	N
Europe	0.22	0.41	0.00	1.00	0.00	1086
Asia	0.53	0.50	0.00	1.00	1.00	1086
Africa	0.12	0.32	0.00	1.00	0.00	1086
North America	0.09	0.29	0.00	1.00	0.00	1086
South America	0.02	0.16	0.00	1.00	0.00	1086
Oceania	0.02	0.12	0.00	1.00	0.00	1086
Asian	0.40	0.49	0.00	1.00	0.00	1086
Age	34.03	10.50	16.00	80.00	31.50	1086
Male	0.92	0.27	0.00	1.00	1.00	1086
Female	0.07	0.25	0.00	1.00	0.00	1086
Non-Binary/Other	0.01	0.10	0.00	1.00	0.00	1086
Edu.	2.57	1.30	0.00	5.00	3.00	1086
Know crypto general	3.51	1.31	0.00	5.00	4.00	1086
Know crypto NFT	0.39	0.49	0.00	1.00	0.00	1086
Risk seeking	0.38	0.49	0.00	1.00	0.00	1086
Works in crypto	0.38	0.49	0.00	1.00	0.00	1086
When interested	67.50	22.37	0.00	100.00	74.10	1029
Wealth inv. Z.	49.05	33.40	0.00	100.00	49.00	1081
BTC share	39.92	32.02	0.00	100.00	35.00	1086
Num. cryptos held	5.12	3.80	0.00	28.00	4.00	1086
Derivatives	0.65	0.48	0.00	1.00	1.00	1086
Farming	0.50	0.50	0.00	1.00	0.00	1086
Taxes	1.53	1.42	0.00	4.00	1.00	1081
Scams	1.77	1.49	0.00	4.00	2.00	1086
Supports crypto	0.19	0.39	0.00	1.00	0.00	1086
Satoshi not betrayed	0.54	0.50	0.00	1.00	1.00	1086
Cryptocurr for spec	0.06	0.23	0.00	1.00	0.00	1086
Own NFT	0.55	0.50	0.00	1.00	1.00	1086

$(0, \pi^2/3)$. In all cases, average marginal effects are presented.

3 Main results

Tables 3, 4, and 5 show the econometric results of estimating Equation (1) for each particular set of variables. In each particular column, we estimate the relationship between a group of independent variables and the main outcome variable (i.e., owning at least one NFT).

3.1 Initial regressions

3.1.1 Socio-economic and risk profile features

The first set of initial results (Table 3, column 1) shows that belonging to Asia, Africa, North America or South America compared to being from Europe (baseline category), reduces the likelihood of investing into NFTs. The opposite relationship is found regarding being from Oceania. Also, NFT owners possess, on average, a lower educational level compared with the general crypto population that do not own NFTs. A higher cryptocurrency knowledge—and in particular, associated with NFTs—is associated with a higher likelihood of owning NFTs. This suggests that individuals with a deeper understanding not only of the cryptocurrency sphere but also of the NFT landscape are more inclined to engage with and invest in NFT assets. Among the crypto population, financial literacy does not play a role with respect to NFT ownership.

Regarding the race to which each respondent associates to, our results suggest that the Asian population is more likely to invest in NFTs compared to the white/Caucasian population. Compared to full-time workers, unemployed people seem to invest more in NFTs. The opposite is found with respect to people that are not working and not looking for work. Finally, compared to risk-averse crypto owners, risk-seeking or risk-neutral do not show any association with owning NFTs. None of the SVO variables are significant compared to the base category (being altruist).

Table 3: Socio-demographic features

	(1)	(2)	(3)
Asia	−0.269 (0.122)*	−0.193 (0.128)	−0.158 (0.099)
Africa	−1.212 (0.264)***	−0.822 (0.092)***	−0.637 (0.085)***
North America	−0.353 (0.061)***	−0.253 (0.042)***	−0.281 (0.025)***
South America	−0.682 (0.251)**	−0.394 (0.109)***	−0.576 (0.067)***
Oceania	0.588 (0.045)***	0.582 (0.023)***	0.338 (0.039)***
Edu.	−0.102 (0.034)**	−0.104 (0.033)**	−0.157 (0.016)***
Age	−0.054 (0.037)	−0.049 (0.035)	
Know crypto NFT	0.989 (0.063)***	0.982 (0.072)***	0.982 (0.091)***
Know crypto general	0.355 (0.102)***	0.346 (0.101)***	0.358 (0.094)***
Know fin.	0.039 (0.044)		
Asian		0.806 (0.223)***	0.828 (0.215)***
Black or of African descent	0.508 (0.410)		
East Asian	0.687 (0.306)*		
South Asian	0.930 (0.134)***		
Southeast Asian	1.453 (0.310)***		
Hispanic or Latino	0.425 (0.365)		
Middle Eastern	0.242 (0.109)*		
Nat Am, Pac Isl, Ind Aus	−0.844 (0.381)*		
Multiracial	0.874 (0.576)		
Not listed	−0.077 (0.323)		
Male		0.401 (0.256)	0.355 (0.212)+
Female	−0.526 (0.267)*		
Non-binary/Other	0.615 (0.467)		
Is working		0.195 (0.228)	0.148 (0.233)
Works in crypto	1.214 (0.202)***	1.207 (0.212)***	1.239 (0.155)***
Part-time	−0.102 (0.223)		
Self-employed	0.204 (0.226)		
Unemployed, looking for work	0.276 (0.073)***		
Unemployed, sickness	0.441 (0.487)		
Not working not looking	−0.335 (0.082)***		
Retired	−0.054 (0.365)		
Risk seeking (binary)		0.214 (0.096)*	0.208 (0.117)+
SVO positive		0.172 (0.136)	
Risk neutral	−0.093 (0.277)		
Risk seeking	0.188 (0.155)		
SVO Competitive	0.164 (0.537)		
SVO Individualist	−0.283 (0.584)		
SVO Prosocial	−0.097 (0.532)		
Obs.	1354	1354	1561

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

In column 2, we aggregate several categorical variables. First, we compare the Asian cryptocurrency owners that we have in our sample[17] versus the non-Asian population. In addition, we compare male crypto owners versus female and non-binary crypto owners. In the first case, Asian crypto owners are more likely to invest in NFTs. In addition, we construct a risk seeking binary variable (being risk seeking versus being risk neutral and risk averse) and a SVO binary variable (*SVO positive*) that aggregates SVO altruist and SVO prosocial. Preliminary results show that those individuals who are more risk seeking are more prone to invest in NFTs.

In column 3, since education and age are jointly influenced by an unmeasured third variable, age is removed from the regression; this is a way of dealing with a possible endogeneity problem.[18] Our educational attainment variable remains significant and negatively correlated with the explained variable. Moreover, column 3 shows the estimated model excluding the variable SVO.[19] Result of the rest of the variables remain robust, with the exception of being male, that now is positively associated with owning NFTs.

3.1.2 Investing profile

The second set of initial results (Table 4, column 1), focuses on the different investing profile variables of crypto owners. The higher is their share of wealth invested in crypto, the higher is the likelihood to invest in NFTs. Preliminary results also suggest that those investors that got interested in crypto in the early stages of cryptocurrencies (variable "when interested"), are more likely to invest in NFTs.[20] In addition, those crypto investors that have more of their crypto portfolio invested in BTC, are also less likely to invest in NFTs. Since crypto derivatives and yield farming can also be considered a “recent” innovation in the digital currencies universe, it is not unexpected that cryptocurrency investors that have used options or other crypto derivatives[21] or that have performed crypto yield farming are more likely to invest in NFTs. However, NFT owners and non-NFT owners show no differences regarding

[17] Asian population agglutinates those ones defined as East Asian, South Asian, and Southeast Asian.

[18] Note that once education is excluded, age is statistically significant (see Table C13 in the Appendix).

[19] Some respondents skipped the questions through which we estimate our SVO variable. That is the reason why the number of available observations for the regression increases.

[20] Since this finding may be counterintuitive compared to the "BTC share" results, we check alternative specifications capturing a non-linear relationship in the "when interested" variable. Once we do this, neither our "when interested" variable nor its square are significant (results not reported for brevity). We thank an anonymous referee for this comment.

[21] Some derivatives, such as cryptocurrency futures, have been used to effectively hedge against inflation expectations and mitigate idiosyncratic market risk (Liu and Valcarcel, 2024).

using leverage to invest in crypto or being a stock/bonds investors. Overconfidence, i.e., the percentage of investors a respondent thinks performed better than her in the previous year to the survey, is not significant.

Table 4: Investing profile features

	(1)	(2)	(3)
Wealth inv. Z	0.215 (0.056)***	0.260 (0.046)***	0.280 (0.055)***
When interested	−0.006 (0.003)+	−0.007 (0.003)*	−0.006 (0.003)*
BTC share	−0.281 (0.083)***	−0.215 (0.064)***	−0.281 (0.061)***
Derivatives	0.595 (0.111)***	0.541 (0.118)***	0.491 (0.125)***
Farming	1.059 (0.223)***	1.045 (0.155)***	1.091 (0.178)***
Leverage	0.063 (0.257)		
Stocks and bonds	−0.137 (0.237)		
Overconfidence	0.043 (0.064)		
Num. cryptos held	0.111 (0.045)*		
MATIC		0.819 (0.061)***	
ETH		0.312 (0.116)**	
SOL		−0.085 (0.245)	
BNB		0.798 (0.079)***	
Num. top 5 cryptos			0.326 (0.081)***
Num. bottom 5 cryptos			0.079 (0.146)
Num.Obs.	1032	1144	1144

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

In column 2, we exclude those variables that were previously not significant and we include a dummy variable for particular tokens such as MATIC, ETH, SOL and BNB - which operate in blockchains that tend to be relevant within the NFT ecosystem.[22] At the same time, we do not include the *number of cryptocurrencies held by an individual* variable because it was constructed using the answers of individuals regarding if they held each particular token. Results show that MATIC, ETH and BNB investors are more likely to own NFTs. Rest of variables remain significant.

In column 3, we perform an analysis splitting our *number of cryptos held* variable. We construct a variable that measures the number of tokens that each person owns or

[22]Additional tokens were incorporated to the regression but they were not significant; results not reported for brevity.

owned depending on whether they are top-5 tokens[23] or bottom-5 tokens.[24] Results show that investors that own or owned the most popular crypto are more likely to invest in NFTs.

3.1.3 Attitudes towards crypto and society

The third set of initial results (Table 5, column 1), focuses on the variables that capture attitudes and opinions of crypto owners towards taxes, crypto scams, trust in the government, risk staking and mass control. Results show that those crypto owners that disagree more on whether cryptocurrency gains should be taxed are less likely to invest in NFTs (this result becomes non-significant once we add additional controls). Column 2 adds variables that measure whether cryptocurrency owners think that crypto has betrayed its original purpose (base category). Those respondents that consider that crypto has not betrayed its original purpose, are more likely to invest in NFTs.

Table 5: Variables that measure attitudes of crypto owners

	(1)	(2)	(3)
Taxes	−0.097 (0.031)**	−0.096 (0.035)**	−0.101 (0.034)**
Scams	−0.121 (0.089)	−0.114 (0.084)	−0.131 (0.075)+
Trust in Gov.	0.310 (0.206)	0.303 (0.209)	0.293 (0.195)
Risk staking	0.016 (0.076)	0.017 (0.077)	0.026 (0.073)
Risk mass control	0.047 (0.033)	0.046 (0.033)	0.048 (0.032)
Purpose Satoshi not betrayed		0.297 (0.103)**	
Purpose Satoshi progress		0.073 (0.111)	
Supports crypto			0.650 (0.089)***
Cryptocurr. for spec.			0.220 (0.405)
Obs.	1435	1421	1420

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Lastly, in column 3 we add two other variables that capture the attitudes and motivations of NFT investors for investing in NFT; namely, we created the "Supports crypto" variable (where the reference category includes all the alternative reasons to invest in crypto rather than "to support the growth of the crypto space") and "Cryptocurr. for spec." variable (where the reference category are all the answers

[23]Measured by market cap at October 2022, these tokens are: BTC, ETH, USDT, USDC, and BNB.

[24]In our survey, at October 2022, bottom-5 are FTT, CRO, XMR, XLM, and ALGO.

excluding "crypto being a means of speculation"). Results show that those crypto owners that have as a primary reason to invest in crypto supporting the growth of the space, are more likely to own NFTs.[25]

3.2 Features of NFT investors: Main regressions

Table 6 (column 1) presents a new set of regressions that include the main variables selected in the "initial results" section. Column 2 presents the same results excluding those variable that were previously non-significant. Compared to the non-NFT owners population, NFT investors show no differences in their gender, when they first became interested in crypto and the share of total portfolio invested in crypto. Nevertheless, among crypto owners, results show that NFT owners possess, on average, a lower educational level compared with the crypto population that do not own NFTs. In particular, moving to a higher educational category decreases the likelihood to invest in NFTs by 18.2 to 19.9 percentage points. We also find that Asian cryptocurrency owners tend to invest more in NFTs than the non-Asian population.

A higher level of cryptocurrency knowledge (getting one extra point in the score related to crypto knowledge increases the probability of investing in crypto from 16% to 19%), especially regarding NFTs, is linked to a greater likelihood of owning NFTs. This finding may indicate that individuals who have a deeper understanding of the NFT landscape are more inclined to engage with and invest in these assets. Moreover, being employed within the cryptocurrency sector further elevates the probability of NFT investment (by 92-96%). Professionals within the crypto industry, through their occupational exposure, may recognize NFTs as viable investment opportunities. Lastly, we present some evidence regarding NFT owners being more risk-seekers than non-NFT owners. The even more extreme volatility and speculative nature of the NFT market may attract individuals with a higher tolerance for financial risk.

Second, compared to the non-NFT owners population, once we are controlling for sociodemographic characteristics and attitudes, NFT investors show no differences in the time when they first got interested in crypto and regarding the share of their wealth they have invested in the crypto sector. As in Table 4, individuals with a higher percentage of total wealth invested in Bitcoin are less likely to invest in NFTs.

[25] In Appendix C.3, we rerun the estimations in Tables 3, 4 and 5 limiting the number of observations to the ones included in the final regression (see following section). Main results remain unchanged.

Traditional Bitcoin investors, who were early adopters of cryptocurrency, may prefer to stay invested in what they perceive as more established assets like Bitcoin, rather than diversifying into the relatively newer and more unstable NFT market.

Table 6: Features of NFT investors: main regressions

	(1)	(2)	(3)
Male	−0.068 (0.268)	0.056 (0.301)	0.062 (0.288)
Edu.	−0.181 (0.036)***	−0.199 (0.025)***	−0.175 (0.024)***
Asian	1.033 (0.157)***	1.084 (0.131)***	1.019 (0.116)***
Know crypto general	0.194 (0.086)*	0.174 (0.092)+	0.157 (0.092)+
Know crypto NFT	1.105 (0.156)***	1.119 (0.116)***	1.045 (0.124)***
Works in crypto	0.931 (0.130)***	0.966 (0.130)***	0.915 (0.134)***
Risk seeking	0.308 (0.125)*	0.294 (0.139)*	0.269 (0.147)+
When interested	−0.003 (0.005)		
Wealth inv. Z	0.121 (0.078)		
ETH			0.217 (0.106)*
MATIC			0.684 (0.120)***
BNB			0.482 (0.111)***
Num. cryptos held	0.114 (0.024)***	0.105 (0.022)***	
BTC share	−0.215 (0.053)***	−0.190 (0.071)**	−0.174 (0.076)*
Derivatives	0.210 (0.098)*	0.326 (0.062)***	0.354 (0.048)***
Farming	0.892 (0.104)***	0.918 (0.110)***	0.906 (0.101)***
Taxes	−0.067 (0.050)		
Scams	−0.162 (0.045)***	−0.159 (0.045)***	−0.168 (0.057)**
Supports crypto	0.560 (0.090)***	0.520 (0.127)***	0.497 (0.125)***
Satoshi not betr.	0.262 (0.078)***	0.284 (0.079)***	0.285 (0.086)***
Cryptocurr. for spec.	0.917 (0.372)*	0.864 (0.329)**	0.893 (0.400)*
Num.Obs.	1019	1086	1086

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Furthermore, owning a higher number of cryptocurrencies is positively associated with a higher likelihood of owning NFTs. Results reveal that individuals engaged in yield farming activities, a practice involving staking or lending cryptocurrencies to earn extra tokens, are more likely to own NFTs. Similarly, our findings stress a positive association between using crypto derivatives and the probability of possessing or have owned NFTs. Both results are statistically significant at 5% and 0.1% significance levels, respectively.

The perception on whether cryptocurrency taxes should be taxed does not differ among NFT and non-NFT owners. On the contrary, our findings indicate that crypto owners with elevated concerns about the potential misuse of cryptocurrency for illicit activities are less likely to engage in the ownership of NFTs. Finally, cryptocurrency investors that think that crypto has not betrayed its original purpose, are more likely to invest in NFTs.[26]

In column 2 and 3, we exclude those variables that were not significant in column 1 and we include the number of cryptocurrencies held and a dummy variable for particular tokens such as MATIC, ETH, SOL and BNB, respectively. Results show that the number of cryptocurrencies held by an individual increases the likelihood of owning NFTs. Furthermore, owning ETH, MATIC, or BNB increases the likelihood of investing in NFTs in 21.7, 68.4 and 48.2 percentage points respectively.

While our analysis is based on overall NFT ownership, the reader may have concerns about whether the findings can be generalized across different types of NFTs, given the diversity in their use cases, value propositions, and investor motivations. Our survey data provide valuable insights into the diversity of NFTs owned by respondents, highlighting the varied nature of this emerging asset class. Among the individuals in the primary regression sample who reported owning NFTs, the distribution of ownership across categories highlights the prominence of certain types, such as art and collectibles. This aligns with the intense media attention during the 2021 market boom, particularly surrounding high-value transactions such as Beeple's Everydays: The First 5000 Days and Pak's The Merge. Hence, the dominance of art and collectible NFTs in our dataset is noteworthy, suggesting that some of our findings may be particularly reflective of the investor profiles associated with these specific NFT types. Art and collectibles are often viewed as speculative assets, with investors drawn by potential financial returns rather than intrinsic utility.

Although our analysis primarily examines NFT ownership as a unified category,

[26] Although both variables "Cryptocurr. for spec." and "Supports crypto" are positive and statistically significant, it is key to mention that they are not capturing the same construct. "Cryptocurr. for spec." represents the primary reason to invest in cryptocurrencies and respondents have to click only on the "main reason". It does not follow that they consider that the entire crypto space should be treated as a speculative object; in section A.3 in the appendix, we provide more explanations about the sentiments of NFTs holders regarding speculation in the NFT world and in the crypto universe in general.

there are strong grounds for generalizing the findings across all NFT types. Fundamentally, NFTs share core characteristics: they are unique digital assets stored on blockchains, tradeable on marketplaces, and generally perceived as speculative investments. These shared features suggest that investor behavior and decision-making processes may exhibit similar patterns across different NFT categories. Thus, while the prominence of art NFTs may skew some results toward this segment, the broader conclusions regarding the demographic and behavioral profiles of NFT investors remain applicable across the entire NFT market.

Nevertheless, we recognize that differences in motivation and use cases may exist among various NFT categories. For example, art and collectibles may attract investors with a preference for aesthetic value or cultural significance, while Utility NFTs or Virtual Land may appeal to those seeking functional or financial utility within digital ecosystems. Future research could build on this work by investigating these category-specific nuances to provide a more granular understanding of NFT investor behavior and preferences.[27]

3.3 Robustness checks

To validate the robustness of our results we performed a number of standard tests (Balietti, 2022) that, for space purposes, we thoroughly document in Appendix B and C.

First, we eliminate those respondents that could be bots. Table C1 presents the new result excluding those observations. The main results are robust. Second, we re-run our main estimation excluding those observations whose IP address location does not match the self-reported country of residence (see Table C2). Results are completely robust, with the exception of the general crypto knowledge variable. In Table C3, we exclude those possible duplicated observations and the main outcomes remain qualitatively unchanged in all the different subsets. Lastly, we delete those individuals whose responses fall into an “unlikely set” (e.g., being retired at a young age). Table C4 shows that results are also robust to this check.

Next, we cluster standard errors by country (see Table C5) and by geografical region (see Table C6). Most results remain robust with the exception of the race category: the binary variable being Asian is no longer significant.

[27]We thank an anonymous referee for this suggestion.

The final robustness check replicates the main regression using a multilevel logit approach approach instead of a simple logit model. Multilevel models may be useful when data are nested within different levels or clusters (in our case, geographical areas), as this approach accounts for the potential correlations within these groups (Peugh, 2010). Table C10 reports the multilevel logistic regression with country nested in continent as random effect; Table C11 presents the multilevel logistic regression with continent as random effect; and Table C12 shows the multilevel logistic regression with country as random effect. In all cases, main results commented along the paper remain solid with the exception of the variable *risk seeking*. Notably, Asian is again significant with this specification.

3.4 Further analysis: The role of age and interaction terms

3.4.1 The role of age

One of the key relationships we examined was the relevance of age and education. Both variables are critical demographic factors that can influence NFT ownership. However, they may be jointly influenced by unmeasured factors such as socioeconomic background or cultural context. In our main specification (Table 6), we included education as a key explanatory variable. Age was excluded to avoid redundancy, as there is a correlation between the two variables — particularly given that younger individuals in the dataset are more likely to be in earlier stages of their educational or professional journey. In Table C13 (reported in section C.5 in the appendix), we include age instead of education. Results show that being younger increases the likelihood of owning NFTs. Our result is robust across different specifications.

Nevertheless, treating age in this way assumes a monotonic relationship with respect to NFT ownership. Hence, we would like to explore if there is a non-monotonic nature of this relationship.[28] We segment the population into two groups: "below 30 years old" versus "30 and above". This specification avoids the restrictive assumption of linearity, aligning with the observed data patterns and offering more intuitive interpretability.

Results in Table 7 show that belonging to the population younger than 30 years old (compared to people older than 30 years old) increases your likelihood of owning a NFT between 44 and 51 percentage points. Therefore, there is a significant but nonlinear relationship with NFT ownership, supporting the idea that younger

[28] We thank an anonymous referee for this suggestion.

investors are more likely to engage in this market.

Table 7: Main regression including Age (<30 years old vs. older population) instead of Education

	(1)	(2)	(3)
Male	−0.058 (0.249)	0.032 (0.255)	0.029 (0.245)
Age (below 30)	0.440 (0.170)**	0.455 (0.178)*	0.507 (0.173)**
Asian	1.021 (0.153)***	1.062 (0.120)***	0.990 (0.093)***
Know crypto general	0.200 (0.079)*	0.178 (0.085)*	0.155 (0.088)+
Know crypto NFT	1.068 (0.166)***	1.089 (0.138)***	1.005 (0.146)***
Works in crypto	0.973 (0.107)***	1.011 (0.137)***	0.945 (0.148)***
Risk seeking	0.319 (0.113)**	0.306 (0.124)*	0.276 (0.134)*
When interested	−0.003 (0.005)		
Wealth inv. Z	0.115 (0.077)		
ETH			0.211 (0.102)*
MATIC			0.767 (0.136)***
BNB			0.519 (0.116)***
Num. cryptos held	0.118 (0.023)***	0.109 (0.022)***	
BTC share	−0.210 (0.058)***	−0.185 (0.075)*	−0.164 (0.084)*
Derivatives	0.182 (0.109)+	0.303 (0.087)***	0.332 (0.074)***
Farming	0.903 (0.118)***	0.933 (0.124)***	0.926 (0.112)***
Taxes	−0.065 (0.057)		
Scams	−0.184 (0.033)***	−0.178 (0.037)***	−0.188 (0.053)***
Supports crypto	0.550 (0.088)***	0.522 (0.134)***	0.504 (0.134)***
Satoshi not betr.	0.250 (0.065)***	0.275 (0.065)***	0.271 (0.069)***
Cryptocurr. for spec.	0.866 (0.323)**	0.797 (0.285)**	0.814 (0.367)*
Num.Obs.	1024	1093	1093

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Recognizing this nonlinearity, we delved deeper into the analysis by dividing age into three categories: younger than 30 years old (base category), 30–50, and older than 50. The estimations show (see Table 8) that people between 30 and 50 years old are between 39% and 46% less likely to own NFTs. These results are even more striking for people older than 50 years old, i.e., they are between 81 and 87% less likely to own NFTs compared to the younger generation.

3.4.2 The role of timing and cost basis in NFT ownership

One intriguing finding in our analysis is the preliminary positive correlation between the length of time respondents have been interested in cryptocurrencies ("when interested") and their likelihood of owning NFTs. The previous relation suggests that

Table 8: Results for different age brakes

Age Range	(1)	(2)	(3)
Age (30,50]	-0.393 (0.180)*	-0.401 (0.186)*	-0.457 (0.180)*
Age (>50)	-0.811 (0.157)***	-0.833 (0.183)***	-0.869 (0.199)***

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant, all the variables included in Table 6 and a continent fixed effect, not reported for brevity.

earlier entrants into the cryptocurrency space might be more inclined to own NFTs. A plausible explanation for this phenomenon lies in the cost basis of cryptocurrencies like ETH and MATIC, which are commonly used to purchase NFT.[29]

Early adopters of cryptocurrencies typically acquired their holdings at a lower cost basis in fiat currency terms. Lower cost basis reduces the perceived expense of purchasing NFTs, as the relative fiat-equivalent value of ETH or MATIC used in transactions remains low. For instance, many NFT marketplaces, such as OpenSea, primarily facilitate transactions using ETH, and Polygon's ecosystem is increasingly popular for NFTs due to lower transaction fees and retail-friendly adoption, as evidenced by Starbucks' integration of Polygon for its Web3 initiatives.[30] Nakavachara and Saengchote (2022) provide supporting evidence for this hypothesis. They find that the dollar-equivalent pricing of The Sandbox's LAND NFTs is higher when the transactions are conducted in SAND (the Sandbox's native cryptocurrency). The pricing disparity may indicate that users with holdings in native cryptocurrencies may perceive NFTs as more affordable, driving higher ownership rates.

To further investigate this relationship, we incorporate interaction terms between the "when interested" variable and our variables related to hold ETH, MATIC, SOL and BNB. We are testing whether the timing of entry into the cryptocurrency space interacts with their holdings of these currencies to influence NFT ownership. Results in Table 9 reveal that the interaction term between "when interested" and ETH holdings is positive and significant at 10 % significance level (see column 1). However, we do not find a statistically significant relation of the other interaction terms (columns 2, 3 and 4).

[29] We are deeply grateful to one annonymous referee for suggesting this analysis.

[30] See https://polygon.technology/blog/starbucks-taps-polygon-for-its-starbucks-r-odyssey-web3-experience-nbsp

This suggestive evidence may highlight the role of timing and cryptocurrency cost basis in shaping NFT ownership patterns. Early adopters of cryptocurrencies, particularly those with ETH holdings, may not only be more familiar with the technological ecosystem but may also perceive NFTs as more affordable due to their lower cost basis in fiat terms.

Table 9: *Interaction between particular tokens and time in crypto*. Logistic regression of investing behavior on having an NFT replicating results of Model 2 in Tab. 4.

	(1)	(2)	(3)	(4)
Wealth inv. Z	0.224 (0.048)***	0.228 (0.047)***	0.228 (0.047)***	0.228 (0.047)***
When interested	−0.004 (0.002)	−0.010 (0.004)**	−0.009 (0.003)**	−0.011 (0.003)***
BTC share	−0.185 (0.086)*	−0.193 (0.087)*	−0.192 (0.087)*	−0.190 (0.083)*
Derivatives	0.440 (0.100)***	0.439 (0.103)***	0.437 (0.100)***	0.432 (0.095)***
Farming	0.995 (0.137)***	1.007 (0.133)***	0.998 (0.135)***	1.008 (0.139)***
MATIC	0.881 (0.057)***	0.485 (0.293)+	0.883 (0.057)***	0.896 (0.055)***
ETH	0.817 (0.278)**	0.314 (0.081)***	0.313 (0.084)***	0.322 (0.082)***
SOL	−0.097 (0.226)	−0.099 (0.227)	−0.456 (0.447)	−0.094 (0.221)
BNB	0.779 (0.083)***	0.792 (0.081)***	0.792 (0.080)***	0.067 (0.515)
When interested&ETH	−0.007 (0.004)+			
When interested&MATIC		0.006 (0.004)		
When interested&SOL			0.005 (0.007)	
When interested&BNB				0.010 (0.007)
Num.Obs.	1024	1024	1024	1024

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

4 Conclusion

NFTs are changing the digital asset landscape, offering unique ownership of digital items such as art, music, and virtual real estate. The rapid evolution and distinctive characteristics of this market, along with the absence of comprehensive research, prompt an exploration into whether the investors engaged in NFTs represent an entirely unique cohort within the broader investment sphere. This paper has tried to fill the gap providing empirical evidence about whether NFT investors constitute a novel class within the realm of digital currencies investment.

Using data from a public survey with global outreach, we uncover several key insights about NFT investors on three macro areas: i) socio-demographics, ii) investing profile, and iii) attitudes towards crypto and society. First, demographically, NFT investors do not differ significantly from non-NFT owners in terms of gender, although NFT owners generally possess a lower educational level compared to the broader crypto investor population who do not own NFTs. In addition, we find that younger individuals are more likely to invest in NFTs. Finally, professionals working within the cryptocurrency industry exhibit a higher propensity to invest in NFTs. Second, in examining their investing profile, our research reveals that those involved in yield farming activities or crypto derivatives are more likely to own NFTs. Third, with regard to their general attitudes towards crypto and society, we find that individuals with heightened concerns about the potential misuse of cryptocurrencies for illicit activities tend to shy away from NFTs. Regarding taxation, there is no significant difference in opinions between NFT owners and non-owners.

While our analysis considers NFT ownership as a unified category, the diversity of NFTs owned by respondents—ranging from art and collectibles to utility tokens and virtual land—demonstrates the multifaceted nature of this market. The prominence of art and collectibles reflects their significant role during the NFT market boom, yet the shared characteristics of NFTs, such as tradeability, uniqueness, and speculative potential, justify the generalization of our findings across categories. We acknowledge, however, that investor motivations may vary between NFT types, with art and collectibles attracting culturally or aesthetically driven investors, while utility-focused NFTs or virtual land may appeal to those engaged in decentralized applications or metaverse ecosystems. Future research could explore these nuances further, providing more granular insights into the evolving NFT landscape and its diverse investor base.

All in all, our findings underscore the distinctive nature of NFT investors within the broader cryptocurrency market. Their unique demographic and investment profiles, coupled with specific attitudes towards risk and regulatory concerns, highlight the need for further research into this emerging class of digital asset investors.

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Appendix

This Appendix provides additional explanations, tables and figures that are also discussed in the paper.

Appendix A: Variables

A.1 Additional variables' description

Table A1 provides additional information about the main variables used in the empirical analysis. The third column presents the categories in which each variable was divided.

A.2 Additional summary statistics and correlations' table

Table A2 presents the main descriptive statistics of the entire sample - considering only observations with a non-blank answer. In addition, table A3 presents correlations among the variables in the main regression of the empirical analysis.

Table A1: Additional variables description and categories

	Socio-economic and risk profile	
Variable	Code	Categories
Education	*Edu*	Less than high school degree; High school degree; Vocational education and training; Bachelor degree (e.g., BA, BS); Master degree (e.g., MA, MS); Doctorate (e.g., PhD, EdD) or professional degree (e.g., Med).
Place of residence	*Country*	Multiple countries.
Race	*Race*	Black or of African descent, East Asian, Hispanic or Latino, Middle Eastern, Multiracial, Native American, Pacific Islander, or Indigenous Australian, South Asian, Southeast Asian, White / Caucasian, Not listed.
Age	*Age*	14 or less; 15-17; 18-21; 22-25; 26-29; 30-33; 34-37; 38-41; 42-45; 46-49; 50-53; 54-57; 58-61; 62-65; 66-69; 70-73; 74-77; 78 or more.
Gender	*Gender*	Male, female, non-binary & other.
Work status	*Is working*	Self-employed; Part-time employed; Full-time employed; Retired; Unemployed: Looking for work; Unemployed: Unable to work due to sickness or ill health; Not working and not looking for work.
Working in crypto	*Works in crypto*	Main occupation; Side job; No.
Cryptocurrency literacy	*Know crypto general*	Index that measures the level of crypto literacy (maximum achievable score: 5).
NFT knowledge	*Know crypto NFT*	Index that measures the level of NFT literacy.
Financial literacy	*Know finance*	Index that measures the level of financial literacy.
Risk seeking	*Risk seeking*	Whether a participant chose to open more than 50 boxes in the Bomb risk elicitation task (Crosetto and Filippin, 2013).
SVO	*SVO*	Social Value Orientation computed as in Murphy et al. (2011).
	Investing profile	
Variable	Code	Categories
Wealth invested in cryptocurrencies	*Wealth inv. Z*	Share of total portfolio invested in crypto, centered and scaled.
Interest in cryptocurrencies	*When interested*	A floating-point number ranging from 0 to 100, where 0 meaning the year-month of the creation of Bitcoin (Jan 2009), and 100 meaning the year month in which we ended our survey (Dec. 2022).
Bitcoin share	*BTC share*	Percentage of overall crypto portfolio in Bitcoin.
Investment in derivatives	*Derivatives*	Yes, No.
Farming	*Farming*	Yes, No.
Leverage	*Leverage*	Yes, No.
Stocks and bonds	*Stocks*	Yes, No.
Overconfidence	*Overconfidence*	Percentage of investors a respondent thinks performed better than her in the previous year (2021).
Number of different cryptocurrencies held	*No. cryptos held*	List of the top 50 cryptocurrencies by market cap at the time the survey was launched: BTC, ETH, USDT, BNB, USDC, XRP, ADA, SOL, AVAX, LUNA, DOT, DOGE, BUSD, SHIB, MATIC, CRO, WBTC, UST, DAI, LTC, ATOM, LINK, NEAR, UNI, TRX, ALGO, BCH, FTT.
	Attitudes towards crypto and society	
Variable	Code	Categories
Taxes	*Taxes*	Completely disagree; to some extent disagree; neither agree nor disagree; to some extent agree; completely agree.
Scams	*Scams*	Likert-5 Agree.
Trust in government	*Trust in gov.*	Likert-5 Agree.
Mass control	*Mass control*	Likert-5 Agree.
Risk staking	*Risk staking*	Likert-5 Agree.
Original purpose of crypto	*Purpose-Satoshi*	Crypto betrayed the original purpose; Different crypto projects may serve different purposes; There is no such a thing as the original purpose of crypto, there is just progress.
Purpose of crypto	*Purpose-you*	Being an alternative to fiat currencies; Coexisting with them; replacing fiat currencies; Being a reserve of value against inflation; Being a means of speculation; Being a means of payment that cannot be censored by governments; Being the fundamental building block of a new type of society living in the metaverse; Other.
Reasons to invest in crypto	*Supports crypto*	To make quick money; To make money with a long-term horizon; To avoid government censorship; To support the growth of the crypto space; Other.
Cryptocurrencies for speculation	*Cryptocurr. for spec.*	From previous "Purpose-you" variable, it takes a value of 1 if the respondent considers that crypto is a means of speculation and 0 otherwise.

Notes: values in Likert-5 Agree are "Completely disagree", "To some extent disagree", "Neither agree nor disagree", "To some extent agree", "completely agree".

Table A2: Descriptive statistics: Entire sample

	Mean	SD	Min	Max	Median	N
Age	33.22	11.78	16.00	80.00	31.50	3744
Male	0.89	0.31	0.00	1.00	1.00	2804
Female	0.09	0.29	0.00	1.00	0.00	2804
Non-Binary/Other	0.02	0.13	0.00	1.00	0.00	2804
Europe	0.19	0.40	0.00	1.00	0.00	2691
Asia	0.00	0.00	0.00	0.00	0.00	1244
Africa	0.00	0.00	0.00	0.00	0.00	2691
North America	0.08	0.28	0.00	1.00	0.00	2691
South America	0.02	0.15	0.00	1.00	0.00	2691
Oceania	0.02	0.13	0.00	1.00	0.00	2691
Asian	0.37	0.48	0.00	1.00	0.00	2760
Edu.	2.49	1.38	0.00	5.00	3.00	2795
Know crypto general	3.06	1.52	0.00	5.00	3.00	2433
Know crypto NFT	0.33	0.47	0.00	1.00	0.00	2433
Risk seeking	0.39	0.49	0.00	1.00	0.00	2423
Works in crypto	0.35	0.48	0.00	1.00	0.00	2749
When interested	70.01	23.47	0.00	100.00	76.51	2496
Wealth inv. Z.	38.33	37.10	0.00	100.00	28.00	2178
BTC share	41.43	32.76	0.00	100.00	37.00	1300
Num. cryptos held	3.53	3.89	0.00	28.00	3.00	2203
Derivatives	0.65	0.48	0.00	1.00	1.00	1683
Farming	0.48	0.50	0.00	1.00	0.00	1706
Taxes	1.69	1.49	0.00	4.00	2.00	1922
Scams	1.97	1.50	0.00	4.00	2.00	1916
Supports crypto	0.19	0.39	0.00	1.00	0.00	1705
Satoshi not betrayed	0.53	0.50	0.00	1.00	1.00	1916
Cryptocurr. for spec.	0.09	0.28	0.00	1.00	0.00	1941
Own NFT	0.54	0.50	0.00	1.00	1.00	1703

Table A3: Correlation table (Obs: 1086)

	Spec	Snb	Sc	Taxes	Scams	Derivatives	Farming	BTC share	Num. cryptos held	Wealth inv. Z	When interested	Risk seeking	Works in crypto	Know crypto NFT	KCG	Asian	Edu.
Male	-.01	.02	.03	-.10**	-.05	-.03	.04	-.01	.12***	.10***	-.04	-.02	.00	.00	.13***	.03	-.05
Edu.	.03	.02	.00	.10**	0.01	-.13***	-.04	-.01	.01	-.06	-.11***	-.12***	-.17***	-.08**	.03	-.14***	
Asian	.00	-.17***	.15***	-.04	.18***	.17***	.15***	.04	.05	.11***	.01	.07	.24***	.21***	.15***		
Know crypto general	-.12***	.08*	.04	-.14***	-.23***	.08	.25***	-.03	.30***	.31***	-.11***	-.08**	.15***	.43***			
Know crypto NFT	-.01	0.00	.07	-.01	-.04	.18***	.20***	.01	.12***	.12***	-.09**	.02	.25***				
Works in crypto	-.02	.03	.07	-.05	-.04	.28***	.23***	-.05	.15***	.18***	-.07	.11***					
Risk seeking	.02	-.02	.08	.02	.03	.06	.00	.03	0.01	.02	.06						
When interested	-.03	.00	-.05	-.02	.02	-.06	-.12***	-.03	-.03	-.04							
Wealth inv. Z	-.11***	.02	.01	-.19***	-.19***	.12***	.16***	.17***	.36***								
Num. cryptos held	-.10***	.09*	.03	-.09*	-.17***	.05	.20***	-.08									
BTC share	.00	-.02	-.04	-.07	-.05	.00	-.06										
Farming	-.01	.00	.08	-.03	-.04	.28***											
Derivatives	.06	-.03	.03	-.02	.07												
Scams	.21***	-.14***	.01	.27***													
Taxes	.19***	-.05	.00														
Sc	-.01	-.07															
Snb	-.04																

Note. Spec: Cryptocurrencies for speculation; Snb: Satoshi not betrayed; Sc: Supports crypto.

A.3 Crypto Attitudes and reasons for owning an NFT

NFT owners—and only NFT owners—in our survey answered the question "What is the primary reason why you own NFTs?". Whereas the answers to this question cannot be used in the main regressions due to endogeneity with the grouping factor, the interpretation of some covariates can benefit from their correlation with the answers to this question. This is particularly useful for variables that are more conceptual, such as those in the "Attitudes towards crypto" set, shown in Table A4.

The answers to Q1 "What is the primary reason why you invest in crypto?" indicate that, non surprisingly, those with a short (long) investment horizon tend to be holding NFTs for short(long)-term gains; within the same question, those who answer that they invest to support the growth of crypto tend to buy NFTs for their personal enjoyment, rather than for the gains, regardless of short or long. In Q2, believing that the main purpose of cryptocurrencies is speculation is uncorrelated with the reasons of holding an NFT; this indicates the two questions are measuring two different constructs (i.e., cryptocurrencies and NFTs), and that the beliefs do not transfer across them. It is worth noting that, because in our sample the vast majority of NFT investors are also cryptocurrencies investors, "Cryptocurrencies for spec." is correlated with "Horizon short" (0.13; $p < 001$) and anticorrelated with "Horizon long" (-0.10; $p < 001$). Finally in Q3, believing that crypto has not betrayed the original purpose by Satoshi Nakamoto—the creator of Bitcoin—is anticorrelated with holding NFTs for short-term gains.

Table A4: Correlation of attitudes variables with reasons for holding an NFT.

Q	Variable	Utility	Enjoy	Short	Long	Collection
Q1	Horizon short	-.06	-0.0	.14***	-.03	-.02
Q1	Horizon long	-.02	-.08*	-.10*	.15***	.03
Q1	Supports crypto	.01	.13***	-.04	-.11**	0.0
Q2	Cryptocurrencies for spec.	-.01	-.01	.07	-.05	.02
Q3	Satoshi not betrayed	.06	-.05	-.10*	.09	-0.0

- Q1: What is the primary reason why you invest in crypto?
- Q2: According to you, the main purpose of cryptocurrencies is:
- Q3: Satoshi Nakamoto created Bitcoin as a response to the economic, financial, and human toll of the 2008 financial crisis. How do you feel about the evolution of crypto?

Appendix B: Data Collection and Curation

We collected all the survey data through the platform State of Crypto (https://stateofcrypto.net) with a customized version of the NodeGame framework (Balietti, 2017). We opened the survey to the general public on Oct 19$^{\text{th}}$ 2022: anyone aged 18 (15 with the permission of their legal guardians) or more could join the study; participation was fully voluntary and responses were not incentivized. We closed the survey upon reaching our preregistered target of 2,000 respondents on Dec 29$^{\text{th}}$ 2022. On average, the survey lasted 14.6 minutes.

B.1 Survey Structure

The State of Crypto Survey 22 spanned through the following sections:

1. *Entry*: age-check, informed consent requested and GDPR informative, bot captcha.
2. *Demographics*: info about participant and relationship to crypto.
3. *Quiz*: knowledge about crypto and traditional financial.
4. *Behavioral*: risk and social preferences.
5. *Investing*: portfolio, investing behavior and confidence.
6. *Societal outcomes*: preferences for inequality, inequality, purpose of crypto.
7. *Predictions*: price, threats, and opportunities.

The full list of questions is available in the anonymized OSF repository: https://osf.io/5xm4d/?view_only=82ab1b433b6e4759a3a510e21f3897ef.

B.2 Ethical and legal clearance

Prior to launching our survey, we preregistered our research at AsPredicted.org https://aspredicted.org/Y31_5RB. Most importantly, we obtained ethical review clearance from the Ethics Committee of the University of Mannheim (EK Mannheim 50/2021) and worked thoroughly with the Data Protection Team of the University of Mannheim to verify the compliance of our methods and infrastructure with the GDPR regulations.

B.3 Recruitment

We recruited participants by promoting the survey with paid ads on social media, mostly on Twitter (now X) via the account @stateof_crypto. In addition, we announced the survey on several other avenues with the following activities:

- direct mails targeted to influential academic and personalities in the crypto space,
- direct mails to influencers in the Financial Independence Retire Early (FIRE) community,
- direct mails to past participants of crypto conferences and events,
- messages in several Telegram and Discord channels about crypto and investing,
- collaborations with local influencers for African communities,
- messages in researchers' and translators' own social networks.

B.4 Data quality

4,871 respondents started the survey, 3,755 passed the initial screening (confirmed their age and solved a captcha) and gave their informed consent for participation, and 2,000 completed it (our preregistration target).

A common technique to improve data quality in surveys are attention checks—also called "instructional manipulation checks" (Oppenheimer et al., 2009). These checks include trap questions with nonsensical items, e.g., 30th February, or instructed response items, e.g., "Please select the third item to this question." However, they are known to have side effects (Balietti, 2022), therefore we decided against their use for two main reasons. First, they degrade user experience and may generate psychological reactance (Brehm, 1966); given that our survey was not incentivized, their use might have significantly increased the dropout rate, reducing power and increasing Type II error (Abbey and Meloy, 2017). Second, attention checks may interfere with research hypotheses and do not rule out confounding variables (Hauser et al., 2018). Therefore, we opted for the post-collection quality checks described below.

Bot detection

In addition to a captcha at the beginning of the survey, we inserted hidden forms, so called "honeypots", in each section of the survey. These forms are invisible to the human eye, but readable by automated software agents that would fill them in, revealing their non-human nature. Overall, only two honeypots have been filled, and we have removed these two observations from all analyses.

Geolocation

We geolocated the IP address of all respondents and compared it with their self-reported country of residence. Two participants claimed to be from Antarctica; this is is highly unlikely and furthermore their IP geo-location did not match their answers, so we removed these two observations from all analyses. The majority (over 25%) of respondents with a mismatch of country of residence/geolocated IP are from China; in China, the use of VPNs software to mask one's own IPs is relatively common in order to access sites not normally accessible. In sum, we define the following set that we later test in the robustness analysis:

- *ip mismatch*: country of residence and IP do not match (obs 402).

Response times

We monitored the response times of participants throughout the survey. We preregistered to exclude participants who take the survey too fast—i.e., more than two standard deviations of the mean—both overall and on each section of the survey. However, some outliers (0.05%) took over one hour to finish the survey, and we decided to exclude them from the computation of the standard deviation. Apart from the age and consent pages, no participant speeded throughout any survey section, therefore we kept the entire sample.

Duplicated responses

Participation to the survey was not gated, anyone with the access link could join it. A cookie would remember if a survey has been already started, but this alone does not ensure that the same person does not participate multiple times. Being the survey unincentivized, the risk is small, nonetheless herein we try to quantify multiple participation, by looking for specific indicators.

Overall, we identified a total of 6.2% of respondents sharing either the same IP address (6%), the same email address (1%), or the same crypto address (0.5%).[31] Sharing the same IP address is not alarming; this is common, for example, for students in the same dorm or even for users of the same Internet Service Provider (ISP) at different physical locations, when IPs are dynamically assigned. Sharing the same crypto or email address is more concerning, but still does not mean per se that the same person took the survey twice. In fact, specially in developing countries, the same physical computer and the same email address could have been shared across members of the same family, relatives, and friends.

To further investigate the issue, we created an index of similarity ranging from zero (fully dissimilar) to one (identical), representing the share of identical answers to the questions in the demographics section of the survey. We computed this index for all pairwise comparisons of respondents not suspected to have taken the survey multiple times (94% of the sample). The average similarity of any two user is about 0.13; considering only those respondents who completed the survey, this number increases to about 0.17. Note that this number indicates a rather low level of similarity between any two users, nonetheless we used it as one of the baselines for the robustness checks in Sec. 4. Here all the sets for potentially duplicated responses:

- *Chance*: similarity score above chance (0.17%; 77 obs);
- *50*: similarity score above 50% (51 obs);
- *75*: similarity score above 75% (9 obs);
- *DG (doppelganger)*: shares either the same email, or the same IP, or the same crypto address with another participant (234 obs).

Unlikely sets of answers

Some responses or combinations of responses are more unlikely than others. We define the following unlikely sets that we later use in the robustness analyses.

- *Ret30*: retired below age 30 (54 obs);
- *Ret50*: retired below age 50 (73 obs);
- *Doc22*: holding a doctorate below age 22 (7 obs);

[31] The sets are overlapping.

- *AllCryptos*: all possible coins reported to be owned (7 obs).
- *BF2std*: bought the first crypto asset more than two standard deviations before claimed to have gotten interested in crypto (6 obs);[32]
- *BF1std*: bought the first crypto asset more than one standard deviations before claimed to have gotten interested in crypto (67 obs).

[32] Small inconsistency is expected because two distinct sliders were used.

Appendix C: Robustness checks

In this section we replicate the main results if Table 6 of the main text with different subsets of the data[33] in Section C.1, and with different model specifications in Section C.2. Overall, results are qualitatively robust to a large set of variations. Section C.3 presents the main regressions included in subsection 3.1 in the main text restricting the sample to just those observations from the final model in subsection 3.2.

C.1 Data Subsets

[33] See Appendix B for more info about the data collection and how we created the data subsets that we test herein.

Table C1: *Dropouts*. Logistic regression of investing behavior on having an NFT replicating results in Tab. 6 without dropouts.

	(1)	(2)	(3)
Male	−0.018 (0.244)	0.090 (0.264)	0.091 (0.255)
Edu.	−0.197 (0.026)***	−0.200 (0.015)***	−0.175 (0.018)***
Asian	1.064 (0.090)***	1.114 (0.067)***	1.044 (0.055)***
Know crypto general	0.199 (0.078)*	0.193 (0.076)*	0.181 (0.073)*
Know crypto NFT	1.059 (0.139)***	1.076 (0.105)***	0.995 (0.112)***
Works in crypto	0.974 (0.139)***	1.009 (0.134)***	0.956 (0.142)***
Risk seeking	0.316 (0.129)*	0.300 (0.160)+	0.272 (0.170)
When interested	−0.003 (0.005)		
Wealth inv. Z	0.119 (0.076)		
ETH			0.212 (0.087)*
MATIC			0.632 (0.118)***
BNB			0.538 (0.101)***
BTC share	−0.223 (0.050)***	−0.196 (0.068)**	−0.183 (0.074)*
Num. cryptos held	0.114 (0.025)***	0.109 (0.023)***	
Derivatives	0.240 (0.088)**	0.356 (0.062)***	0.377 (0.053)***
Farming	0.888 (0.095)***	0.908 (0.103)***	0.901 (0.096)***
Scams	−0.164 (0.047)***	−0.168 (0.048)***	−0.177 (0.061)**
Taxes	−0.069 (0.057)		
Supports crypto	0.567 (0.097)***	0.503 (0.110)***	0.479 (0.114)***
Satoshi not betr.	0.243 (0.080)**	0.228 (0.095)*	0.227 (0.098)*
Cryptocurr for spec.	0.905 (0.388)*	0.870 (0.348)*	0.880 (0.425)*
Num.Obs.	998	1059	1059

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Table C2: *Geolocation.* Logistic regression of investing behavior on having an NFT; replicating results of Table 6 without respondents with mismatching of geolocated IP, as defined in subsection A.3.

	(1)	(2)	(3)
Male	0.130 (0.304)	0.303 (0.312)	0.307 (0.311)
Edu.	−0.182 (0.054)***	−0.205 (0.027)***	−0.184 (0.031)***
Asian	1.179 (0.109)***	1.188 (0.106)***	1.116 (0.093)***
Know crypto general	0.177 (0.113)	0.149 (0.128)	0.132 (0.129)
Know crypto NFT	1.192 (0.241)***	1.207 (0.191)***	1.122 (0.208)***
Works in crypto	1.045 (0.201)***	1.029 (0.156)***	0.971 (0.160)***
Risk seeking	0.376 (0.125)**	0.395 (0.156)*	0.357 (0.154)*
When interested	−0.001 (0.007)		
Wealth inv. Z	0.166 (0.078)*		
ETH			0.215 (0.127)+
MATIC			0.624 (0.124)***
BNB			0.502 (0.104)***
BTC share	−0.186 (0.051)***	−0.161 (0.074)*	−0.152 (0.078)+
Num. cryptos held	0.114 (0.022)***	0.111 (0.020)***	
Derivatives	0.348 (0.125)**	0.448 (0.115)***	0.455 (0.101)***
Farming	0.913 (0.135)***	0.924 (0.137)***	0.937 (0.130)***
Scams	−0.159 (0.037)***	−0.158 (0.041)***	−0.171 (0.053)**
Taxes	−0.089 (0.041)*		
Supports crypto	0.526 (0.093)***	0.474 (0.182)**	0.456 (0.165)**
Satoshi not betr.	0.273 (0.100)**	0.284 (0.099)**	0.287 (0.105)**
Speculator	1.088 (0.495)*	0.960 (0.459)*	1.009 (0.533)+
Num.Obs.	866	920	920

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Table C3: *Duplication.* Logistic regression of investing behavior on having an NFT; replicating results of Model 2 in Tab. 6 without potentially duplicated responses, as defined in subsection A.3.

	DG	Chance	50	75
Male	0.091 (0.290)	0.051 (0.290)	0.072 (0.286)	0.064 (0.307)
Edu	−0.193 (0.023)***	−0.195 (0.024)***	−0.192 (0.021)***	−0.196 (0.023)***
Asian	1.074 (0.182)***	1.060 (0.146)***	1.052 (0.144)***	1.084 (0.133)***
Know crypto general	0.168 (0.073)*	0.172 (0.077)*	0.170 (0.084)*	0.176 (0.091)+
Know crypto NFT	1.121 (0.120)***	1.108 (0.107)***	1.115 (0.103)***	1.135 (0.108)***
Works in crypto	0.911 (0.158)***	0.971 (0.133)***	0.966 (0.133)***	0.971 (0.132)***
Risk seeking	0.333 (0.115)**	0.292 (0.125)*	0.310 (0.134)*	0.309 (0.127)*
Num. cryptos held	0.112 (0.018)***	0.104 (0.020)***	0.105 (0.022)***	0.107 (0.023)***
BTC share	−0.178 (0.065)**	−0.190 (0.064)**	−0.190 (0.069)**	−0.194 (0.068)**
Derivatives	0.333 (0.061)***	0.323 (0.061)***	0.335 (0.070)***	0.338 (0.063)***
Farming	0.914 (0.113)***	0.935 (0.129)***	0.938 (0.121)***	0.921 (0.107)***
Scams	−0.141 (0.048)**	−0.144 (0.050)**	−0.151 (0.047)**	−0.157 (0.045)***
Supports crypto	0.547 (0.180)**	0.542 (0.150)***	0.529 (0.147)***	0.514 (0.121)***
Satoshi not betr.	0.362 (0.103)***	0.352 (0.081)***	0.329 (0.071)***	0.293 (0.074)***
Cryptocurr. for spec.	0.911 (0.438)*	0.870 (0.374)*	0.899 (0.347)**	0.857 (0.330)**
Num.Obs.	1021	1056	1067	1084

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Table C4: *Unlikely sets.* Logistic regression of investing behavior on having an NFT; replicating results of Model 2 in Tab. 6 without respondents in unlikely sets, as defined in subsection A.3.

	Ret30	Ret50	Doc22	AllCryptos	BF1std	BF2std
Male	0.065	0.064	0.044	0.044	0.058	0.186
	(0.308)	(0.314)	(0.297)	(0.297)	(0.302)	(0.307)
Edu	−0.208***	−0.204***	−0.206***	−0.206***	−0.198***	−0.198***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.024)	(0.024)
Asian	1.044***	1.018***	1.104***	1.104***	1.087***	1.036***
	(0.124)	(0.119)	(0.136)	(0.136)	(0.133)	(0.115)
Know crypto general	0.180+	0.188+	0.180*	0.180*	0.174+	0.188*
	(0.098)	(0.101)	(0.091)	(0.091)	(0.093)	(0.087)
Know crypto NFT	1.122***	1.130***	1.112***	1.112***	1.115***	1.079***
	(0.119)	(0.122)	(0.114)	(0.114)	(0.116)	(0.126)
Works in crypto	0.952***	0.946***	0.958***	0.958***	0.963***	0.991***
	(0.135)	(0.145)	(0.134)	(0.134)	(0.131)	(0.123)
Risk seeking	0.272*	0.285*	0.296*	0.296*	0.292*	0.279*
	(0.135)	(0.136)	(0.131)	(0.131)	(0.139)	(0.138)
Num. cryptos held	0.107***	0.108***	0.108***	0.108***	0.105***	0.106***
	(0.021)	(0.022)	(0.023)	(0.023)	(0.022)	(0.023)
BTC share	−0.187**	−0.195*	−0.191**	−0.191**	−0.190**	−0.174*
	(0.072)	(0.080)	(0.070)	(0.070)	(0.070)	(0.070)
Derivatives	0.334***	0.333***	0.309***	0.309***	0.332***	0.295***
	(0.061)	(0.039)	(0.061)	(0.061)	(0.061)	(0.040)
Farming	0.887***	0.888***	0.906***	0.906***	0.913***	0.915***
	(0.105)	(0.108)	(0.117)	(0.117)	(0.110)	(0.117)
Scams	−0.149**	−0.146**	−0.161***	−0.161***	−0.157***	−0.140**
	(0.048)	(0.045)	(0.044)	(0.044)	(0.045)	(0.047)
Supports crypto	0.526***	0.490***	0.526***	0.526***	0.517***	0.554***
	(0.123)	(0.138)	(0.127)	(0.127)	(0.128)	(0.115)
Satoshi not betr.	0.259***	0.241***	0.301***	0.301***	0.281***	0.252*
	(0.069)	(0.067)	(0.074)	(0.074)	(0.078)	(0.103)
Cryptocurr. for spec.	0.872**	0.861**	0.902**	0.902**	0.858**	0.913**
	(0.337)	(0.334)	(0.349)	(0.349)	(0.328)	(0.303)
Num.Obs.	1077	1072	1082	1082	1084	1055

Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

C.2 Alternative models

Given that in Table 6 we use clustered standard errors (and fixed effects) on continent, we try different clustering specifications - for example, by country and by geographical region. For the latter, we associated countries to regions as in the list below. Furthermore, we tried three additional region specifications, in which: (i) we aggregated the Caribbean and Central America regions into North America and South America, (ii) we associated Israel and Cyprus to Europe instead of Asia, and (iii) we associated Russia with Asia instead of Europe. The results are robust across these different specifications, which for brevity we do not report here.

- **Africa**: Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Rep., Congo, Côte d'Ivoire, Dem. Rep. Congo, Eq. Guinea, Eritrea, eSwatini, Ethiopia, Gabon, Ghana, Guinea, Kenya, Lesotho, Libya, Madagascar, Malawi, Mauritania, Mauritius, Morocco, Mozambique, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe.
- **Caribbean**: Antigua and Barbuda, Bahamas, Bermuda, Bonaire, Sint Eustatius and Saba, Cuba, Dominica, Haiti, Martinique, Montserrat, Sint Maarten (Dutch part), Trinidad and Tobago, Turks and Caicos Islands, Virgin Islands, British.
- **Central America**: Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama.
- **Central Asia**: Azerbaijan, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan East Asia, China, Hong Kong, Japan, Macao, Mongolia, North Korea, South Korea, Taiwan.
- **Europe**: Åland Islands, Albania, Andorra, Austria, Belarus, Belgium, Bosnia and Herz., Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Gibraltar, Greece, Guernsey, Hungary, Iceland, Ireland, Isle of Man, Italy, Latvia, Lithuania, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom.
- **Middle East**: Afghanistan, Armenia, Cyprus, Egypt, Georgia, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Palestine, Qatar, Saudi Arabia, Syria, Turkey, United Arab Emirates, Yemen.

- **North America**: Canada, Mexico, United States of America.
- **Oceania**: American Samoa, Australia, Cook Island, Fiji, Heard Island and McDonald Islands, "Micronesia, Federated States of", New Caledonia, New Zealand, Norfolk Island, Tonga, Tuvalu, Vanuatu.
- **South, America**: Argentina, Brazil, Chile, Colombia, Ecuador, French Guiana, Paraguay, Uruguay, Venezuela.
- **South Asia**: Bangladesh, Bhutan, India, Nepal, Pakistan, Sri Lanka.
- **Southeast Asia**: British Indian Ocean Territory, Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, Vietnam.

Table C5: *Country std. err.* Logistic regression of investing behavior on having an NFT replicating results in Tab. 6 with country fixed effect and standard errors clustered on country (instead of continent).

	(1)	(2)	(3)
Male	−0.095 (0.323)	0.046 (0.319)	0.112 (0.319)
Edu.	−0.162 (0.071)*	−0.192 (0.066)**	−0.177 (0.068)**
Asian	0.039 (0.413)	0.081 (0.375)	0.039 (0.369)
Know crypto general	0.158 (0.058)**	0.139 (0.055)*	0.132 (0.056)*
Know crypto NFT	1.085 (0.195)***	1.111 (0.182)***	1.052 (0.181)***
Works in crypto	0.855 (0.263)**	0.824 (0.239)***	0.767 (0.238)**
Risk seeking	0.187 (0.175)	0.196 (0.181)	0.212 (0.177)
When interested	−0.002 (0.004)		
Wealth inv. Z	0.072 (0.097)		
ETH			0.250 (0.153)
MATIC			0.596 (0.198)**
BNB			0.394 (0.169)*
BTC share	−0.223 (0.097)*	−0.210 (0.100)*	−0.212 (0.094)*
Num. cryptos held	0.124 (0.025)***	0.115 (0.022)***	
Derivatives	0.150 (0.193)	0.301 (0.181)+	0.331 (0.181)+
Farming	1.020 (0.195)***	1.010 (0.190)***	1.039 (0.170)***
Scams	−0.166 (0.065)*	−0.180 (0.065)**	−0.202 (0.062)**
Taxes	−0.118 (0.071)+		
Supports crypto	0.733 (0.235)**	0.617 (0.220)**	0.561 (0.213)**
Satoshi not betr.	0.266 (0.156)+	0.274 (0.149)+	0.260 (0.153)+
Cryptocurr. for spec.	0.995 (0.571)+	0.989 (0.551)+	1.015 (0.595)+
Num.Obs.	1019	1086	1086

Average marginal effects presented. Standard errors clustered by country are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a country fixed effect, not reported for brevity.

Table C6: *Region CA std. err.* Logistic regression of investing behavior on having an NFT replicating results in Tab. 6 with region ca fixed effect and standard errors clustered on region ca (instead of continent).

	(1)	(2)	(3)
Male	−0.051 (0.343)	0.078 (0.344)	0.087 (0.321)
Edu.	−0.139 (0.048)**	−0.162 (0.037)***	−0.143 (0.038)***
Asian	0.312 (0.349)	0.444 (0.289)	0.403 (0.287)
Know crypto general	0.148 (0.075)*	0.130 (0.073)+	0.115 (0.072)
Know crypto NFT	1.022 (0.164)***	1.040 (0.122)***	0.980 (0.121)***
Works in crypto	0.868 (0.183)***	0.905 (0.179)***	0.871 (0.178)***
Risk seeking	0.269 (0.112)*	0.256 (0.137)+	0.242 (0.137)+
When interested	−0.003 (0.005)		
Wealth inv. Z	0.110 (0.087)		
ETH			0.228 (0.118)+
MATIC			0.709 (0.123)***
BNB			0.447 (0.133)***
BTC share	−0.245 (0.092)**	−0.204 (0.105)+	−0.194 (0.101)+
Num. cryptos held	0.121 (0.019)***	0.110 (0.017)***	
Derivatives	0.237 (0.112)*	0.367 (0.092)***	0.397 (0.085)***
Farming	0.835 (0.123)***	0.877 (0.119)***	0.875 (0.108)***
Scams	−0.183 (0.039)***	−0.176 (0.042)***	−0.191 (0.045)***
Taxes	−0.086 (0.068)		
Supports crypto	0.545 (0.102)***	0.503 (0.119)***	0.463 (0.135)***
Satoshi not betr.	0.231 (0.066)***	0.243 (0.070)***	0.235 (0.071)**
Cryptocurr. for spec.	0.997 (0.573)+	0.935 (0.495)+	0.956 (0.563)+
Num.Obs.	1019	1086	1086

Average marginal effects presented. Standard errors clustered by region are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a region fixed effect, not reported for brevity.

C.3 Initial regressions with observations from final model

Herein, we replicate the results of the initial regressions in Tables 3, 4, 5 with only the observations used in the joint regressions in Table 6.

Table C7: *Socio-demographics features*. Logistic regression replicating the results in Tab. 3 using only observations from Model 2 in Tab. 6.

	(1)	(2)	(3)
Asia	−0.324 (0.280)	−0.213 (0.163)	−0.174 (0.127)
Africa	−1.060 (0.210)***	−0.976 (0.128)***	−0.747 (0.094)***
North America	−0.552 (0.068)***	−0.386 (0.035)***	−0.419 (0.014)***
South America	−1.250 (0.156)***	−0.694 (0.143)***	−0.840 (0.059)***
Oceania	0.320 (0.050)***	0.252 (0.067)***	0.069 (0.064)
Edu.	−0.173 (0.015)***	−0.142 (0.031)***	−0.180 (0.021)***
Age	−0.022 (0.051)	−0.021 (0.043)	
Know crypto NFT	1.045 (0.073)***	0.993 (0.068)***	1.010 (0.086)***
Know crypto general	0.339 (0.131)**	0.324 (0.132)*	0.362 (0.126)**
Know fin.	0.005 (0.055)		
Asian		0.920 (0.260)***	0.896 (0.225)***
Black or of African descent	−0.072 (0.353)		
East Asian	0.772 (0.483)		
South Asian	1.440 (0.310)***		
Southeast Asian	1.567 (0.456)***		
Hispanic or Latino	0.725 (0.284)*		
Middle Eastern	0.739 (0.276)**		
Nat Am, Pac Isl, Ind Aus	−0.907 (0.456)*		
Multiracial	1.164 (0.767)		
Not listed	−0.250 (0.511)		
Male		0.356 (0.274)	0.235 (0.227)
Female	−0.304 (0.322)		
Non-binary/Other	0.034 (0.547)		
Is working		0.257 (0.191)	0.250 (0.196)
Works in crypto	1.212 (0.156)***	1.203 (0.176)***	1.203 (0.120)***
Part-time	0.119 (0.205)		
Self-employed	0.308 (0.209)		
Unemployed, looking for work	0.509 (0.190)**		
Unemployed, sickness	0.406 (0.627)		
Not working not looking	−0.642 (0.139)***		
Retired	−0.573 (0.315)+		
Risk seeking (binary)		0.299 (0.130)*	0.323 (0.146)*
SVO positive		0.028 (0.193)	
Risk neutral	−0.081 (0.297)		
Risk Seeking	0.236 (0.160)		
SVO Competitive	−0.698 (1.348)		
SVO Individualist	−1.444 (1.401)		
SVO Prosocial	−1.365 (1.478)		
Num.Obs.	961	961	1080

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Table C8: *Investing profile.* Logistic regression replicating the results in Tab. 4 using only observations from Model 2 in Tab. 6.

	(1)	(2)	(3)
Wealth inv. Z	0.188 (0.068)**	0.228 (0.047)***	0.248 (0.055)***
When interested	−0.007 (0.004)+	−0.008 (0.003)*	−0.007 (0.003)*
BTC share	−0.266 (0.106)*	−0.191 (0.087)*	−0.258 (0.081)**
Derivatives	0.541 (0.126)***	0.434 (0.104)***	0.375 (0.115)**
Farming	1.044 (0.199)***	0.999 (0.134)***	1.052 (0.153)***
Leverage	−0.033 (0.266)		
Stocks and Bonds	−0.099 (0.241)		
Overconfidence	0.020 (0.062)		
Num. cryptos held	0.120 (0.037)**		
MATIC		0.878 (0.055)***	
ETH		0.312 (0.083)***	
SOL		−0.102 (0.228)	
BNB		0.786 (0.083)***	
Num. top 5 cryptos			0.334 (0.079)***
Num. bottom 5 cryptos			0.089 (0.147)
Num.Obs.	939	1024	1024

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Table C9: *Attitudes towards crypto and society*. Logistic regression replicating the results in Tab. 5 using only observations from Model 2 in Tab. 6.

	(1)	(2)	(3)
Taxes	−0.063 (0.040)	−0.062 (0.042)	−0.073 (0.044)+
Scams	−0.130 (0.058)*	−0.119 (0.059)*	−0.156 (0.054)**
Trust in Gov.	0.266 (0.218)	0.268 (0.219)	0.251 (0.218)
Risk staking	0.004 (0.085)	0.001 (0.085)	0.019 (0.083)
Risk mass control	0.041 (0.027)	0.042 (0.030)	0.041 (0.024)+
Purpose Satoshi not betrayed		0.263 (0.099)**	
Purpose Satoshi progress		−0.043 (0.115)	
Supports crypto			0.666 (0.108)***
Cryptocurr. for spec.			0.713 (0.331)*
Num.Obs.	1060	1060	1060

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

C.4 Multilevel regressions

Table C10: *Continent/country.* Multilevel logistic regression with country nested in continent as random effect replicating results in Tab. 6

	(1)	(2)	(3)
Male	−0.105 (0.321)	0.021 (0.312)	0.050 (0.313)
Edu.	−0.142 (0.070)*	−0.162 (0.066)*	−0.146 (0.066)*
Asian	0.532 (0.300)+	0.581 (0.287)*	0.602 (0.293)*
Know crypto general	0.165 (0.078)*	0.144 (0.074)+	0.136 (0.075)+
Know crypto NFT	0.979 (0.195)***	0.988 (0.189)***	0.925 (0.189)***
Works in crypto	0.810 (0.204)***	0.841 (0.194)***	0.795 (0.194)***
Risk seeking	0.206 (0.181)	0.199 (0.174)	0.202 (0.174)
When interested	−0.003 (0.004)		
Wealth inv. Z	0.135 (0.094)		
ETH			0.292 (0.188)
MATIC			0.674 (0.192)***
BNB			0.447 (0.183)*
BTC share	−0.231 (0.089)**	−0.207 (0.085)*	−0.195 (0.085)*
Num. cryptos held	0.124 (0.026)***	0.117 (0.025)***	
Derivatives	0.190 (0.194)	0.333 (0.186)+	0.354 (0.185)+
Farming	0.880 (0.179)***	0.902 (0.173)***	0.899 (0.172)***
Scams	−0.170 (0.064)**	−0.175 (0.061)**	−0.190 (0.061)**
Taxes	−0.078 (0.062)		
Supports crypto	0.599 (0.219)**	0.546 (0.212)*	0.492 (0.211)*
Satoshi not betr.	0.226 (0.175)	0.255 (0.169)	0.249 (0.169)
Cryptocurr. for spec.	1.004 (0.417)*	0.952 (0.394)*	0.983 (0.401)*
Num.Obs.	1019	1086	1086
R2 Marg.	0.387	0.387	0.407
R2 Cond.	0.464	0.458	0.460
AIC	1006.6	1061.8	1062.3
BIC	1110.0	1151.6	1162.1
ICC	0.1	0.1	0.1
RMSE	0.38	0.38	0.38
Std.Errors	IID	IID	IID

The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant not reported for brevity.

Table C11: *Continent.* Multilevel logistic regression with continent as random effect replicating results in Tab. 6

	(1)	(2)	(3)
Male	−0.085 (0.309)	0.030 (0.300)	0.028 (0.303)
Edu.	−0.173 (0.066)**	−0.191 (0.063)**	−0.169 (0.063)**
Asian	1.118 (0.222)***	1.162 (0.210)***	1.122 (0.220)***
Know crypto general	0.217 (0.075)**	0.200 (0.071)**	0.187 (0.076)*
Know crypto NFT	1.089 (0.187)***	1.108 (0.180)***	1.027 (0.182)***
Works in crypto	0.845 (0.195)***	0.879 (0.186)***	0.795 (0.205)***
Risk seeking	0.281 (0.172)	0.266 (0.165)	0.244 (0.168)
When interested	−0.003 (0.004)		
Wealth inv. Z	0.136 (0.090)		
ETH			0.321 (0.191)+
MATIC			0.698 (0.182)***
BNB			0.454 (0.172)**
BTC share	−0.213 (0.085)*	−0.185 (0.081)*	−0.164 (0.082)*
Num. cryptos held	0.115 (0.024)***	0.107 (0.023)***	
Derivatives	0.168 (0.186)	0.285 (0.178)	0.301 (0.180)+
Farming	0.861 (0.170)***	0.889 (0.163)***	0.869 (0.166)***
Scams	−0.169 (0.061)**	−0.163 (0.058)**	−0.175 (0.058)**
Taxes	−0.053 (0.059)		
Supports crypto	0.556 (0.207)**	0.517 (0.200)**	0.479 (0.201)*
Satoshi not betr.	0.261 (0.166)	0.286 (0.160)+	0.284 (0.161)+
Cryptocurr. for spec.	0.939 (0.395)*	0.891 (0.375)*	0.954 (0.385)*
Num.Obs.	1019	1086	1086
R2 Marg.	0.471	0.475	0.485
R2 Cond.	0.483	0.482	0.487
AIC	1024.0	1081.9	1075.8
BIC	1122.5	1166.7	1170.6
ICC	0.0	0.0	0.0
RMSE	0.40	0.40	0.40
Std.Errors	IID	IID	IID

The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant not reported for brevity.

Table C12: *Country.* Multilevel logistic regression with country as random effect replicating results in Tab. 6

	(1)	(2)	(3)
Male	−0.110 (0.321)	0.017 (0.312)	0.048 (0.313)
Edu.	−0.138 (0.070)*	−0.160 (0.066)*	−0.146 (0.066)*
Asian	0.677 (0.269)*	0.685 (0.255)**	0.678 (0.253)**
Know crypto general	0.177 (0.077)*	0.152 (0.073)*	0.140 (0.074)+
Know crypto NFT	0.967 (0.194)***	0.984 (0.188)***	0.921 (0.189)***
Works in crypto	0.758 (0.198)***	0.807 (0.189)***	0.772 (0.188)***
Risk seeking	0.194 (0.180)	0.193 (0.173)	0.201 (0.174)
When interested	−0.003 (0.004)		
Wealth inv. Z	0.146 (0.094)		
ETH			0.308 (0.184)+
MATIC			0.680 (0.191)***
BNB			0.444 (0.182)*
BTC share	−0.229 (0.089)*	−0.204 (0.085)*	−0.193 (0.085)*
Num. cryptos held	0.125 (0.026)***	0.118 (0.025)***	
Derivatives	0.171 (0.193)	0.323 (0.185)+	0.349 (0.184)+
Farming	0.872 (0.179)***	0.897 (0.172)***	0.894 (0.172)***
Scams	−0.175 (0.064)**	−0.179 (0.061)**	−0.192 (0.061)**
Taxes	−0.069 (0.061)		
Supports crypto	0.600 (0.219)**	0.545 (0.212)*	0.489 (0.210)*
Satoshi not betr.	0.226 (0.175)	0.257 (0.169)	0.248 (0.168)
Cryptocurr. for spec.	1.027 (0.416)*	0.970 (0.393)*	0.998 (0.399)*
SD (Intercept country_country)	0.639	0.626	0.548
Num.Obs.	1019	1086	1086
R2 Marg.	0.397	0.394	0.412
R2 Cond.	0.463	0.459	0.461
AIC	1006.1	1060.5	1060.5
BIC	1104.6	1145.3	1155.3
ICC	0.1	0.1	0.1
RMSE	0.38	0.38	0.38
Std.Errors	IID	IID	IID

The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant not reported for brevity.

C.5 Results associated to age

Table C13: *Age*. Logistic regression of investing behavior on having an NFT; replicating results of Model 2 in Tab. 6 including Age instead of Education.

	(1)	(2)	(3)
Male	−0.087 (0.238)	0.004 (0.243)	0.002 (0.233)
Age	−0.062 (0.030)*	−0.075 (0.041)+	−0.074 (0.042)+
Asian	1.057 (0.164)***	1.091 (0.124)***	1.025 (0.095)***
Know crypto general	0.193 (0.077)*	0.170 (0.085)*	0.150 (0.088)+
Know crypto NFT	1.092 (0.168)***	1.110 (0.141)***	1.025 (0.147)***
Works in crypto	0.952 (0.119)***	0.991 (0.146)***	0.928 (0.155)***
Risk seeking	0.322 (0.114)**	0.306 (0.126)*	0.275 (0.138)*
When interested	−0.003 (0.004)		
Wealth inv. Z	0.116 (0.072)		
ETH			0.216 (0.101)*
MATIC			0.749 (0.144)***
BNB			0.520 (0.114)***
Num. cryptos held	0.119 (0.022)***	0.111 (0.020)***	
BTC share	−0.208 (0.057)***	−0.180 (0.079)*	−0.161 (0.087)+
Derivatives	0.183 (0.117)	0.299 (0.098)**	0.333 (0.084)***
Farming	0.880 (0.116)***	0.913 (0.123)***	0.901 (0.113)***
Taxes	−0.067 (0.055)		
Scams	−0.178 (0.036)***	−0.174 (0.039)***	−0.184 (0.054)***
Supports crypto	0.537 (0.081)***	0.505 (0.133)***	0.486 (0.128)***
Satoshi not betr.	0.260 (0.068)***	0.283 (0.070)***	0.279 (0.073)***
Cryptocurr. for spec.	0.867 (0.334)**	0.793 (0.292)**	0.818 (0.377)*
Num.Obs.	1024	1093	1093

The table reports the results of the estimation of the logit regression. The dependent variable is the ownership of NFTs. See Table 1 for the definition of variables. Average marginal effects presented. Standard errors clustered by continent are reported in parentheses. The symbols ***, **, *, and + indicate statistical significance at the 0.1%, 1%, 5% and 10% level, respectively. The models include also a constant and a continent fixed effect, not reported for brevity.

Appendix D: More details on the preregistration

We have preregistered the following research question at AsPredicted.org (https://aspredicted.org/Y31_5RB): *Are NFT investors a completely new class of investors?*

We then articulate our main question in the following hypotheses:

H1. NFT users do not differ from non-NFT users in their sociodemographic profile (age, gender, education, financial education).

H2. NFT & crypto owners are less (more) prone to speculate and have a longer (shorter) investment horizon / other motivation.

H3. NFT users have less concerns with respect to non-NFT users regarding crypto facilitates money laundering and other scams.

H4. There is a difference in the perception regarding whether cryptocurrency gains should be taxed.

Deviations from preregistration

We explain and motivate here a number of deviations from our preregistered analysis plan.

- We dropped the analysis for the groups of "Just NFT owners" vs. "non-NFT owners" due to the paucity of respondents who claimed to hold NFTs only (i.e., no cryptos).
- We have split the crypto literacy index into two variables, "Know crypto general" and "Know crypto NFT" to better reflects to differences in contextual knowledge about NFTs. The latter includes one question about NFTs, and the rest formed the "general" index.
- We have dropped the covariate "Preferences for redistribution" because not significant.
- We have included more variables related the investing profile of NFT owners.
- We have presented the results in the main text with standard errors clustered by continent, instead of country, because some countries would have only one observation; however, we reported results in the Appendix for different clustering specifications, including multi-level models.

- We have dropped the covariate “Short investment horizon” because it was not significant in the joint models and adopted three other variables for a more fine grained analyses of the attitudes of investors, namely “Satoshi not betrayed”, “Cryptocurrencies for speculation”, and “Supports crypto” (see Section A.3 for more details).