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Are crypto and non-crypto investors alike? Evidence from a comprehensive survey in Brazil

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ABSTRACT

Cryptocurrencies and blockchain have become a global phenomenon, transforming people's relationships with technology and offering innovative tools for businesses and individuals to strive in a digital age. However, little is still known about the main drivers of cryptocurrency ownership, especially in emerging markets. Based on a representative online survey among 573 Brazilian digital platform investors, we find that crypto investors tend to be young, male, more tolerant to risk, less optimistic in their economic views, and consider themselves as 'better' investors compared to non-crypto online traders. While crypto and non-crypto investors have similar educational backgrounds, our results show that cryptocurrency literacy positively and strongly relates to cryptocurrency ownership and intentions to invest in cryptocurrency. A gender gap among cryptocurrency investors has been confirmed. The findings further suggest that sophisticated in-vestors are more likely to hedge pessimistic economic expectations using cryptocurrency than their unsophisticated peers. We also find significant heterogeneity among cryptocurrency investors (e.g., early x late adopters) on attitudes and beliefs. The insights into digital investors' intentions to invest in cryptocurrency can be valuable for policymakers in designing strategies for the broader adoption of digital assets in the era of a decentralized economy, considering the planned adoption of CBDC in Brazil.

1. Introduction

Over the past decade, cryptocurrencies have reinforced their role as a new alternative asset class and have gained increasing popularity among online investors around the globe. Notably, the range of digital applications built on blockchain technology has advanced, offering society new investment assets and tools for developing innovative business models based on decentralization and digitization. As new applications built in tokenization, Decentralized finance (DeFi), and central bank digital currencies (CBDCs) may revolutionize the way individuals, companies, and governments interact in the financial markets [1], it is unsurprisingly that the adoption of crypto-assets and their potential effects on the democratization of access to financial services is part of the Davos Agenda [2,3]. [4] demonstrated the impact of CBDC uncertainty on both digital and traditional assets using in-novative news-based indexes. These effects of uncertainty are in line with findings reported by Ref. [5]. In Brazil, active discussions regarding the introduction of CBDC have been prominent in the media, and the public use of central bank digital currency is planned to commence in 2024[2], positioning Brazil as one of the pioneers in CBDC adoption. Therefore, it is essential to

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[2] Please see https://www.reuters.com/world/americas/brazil-announces-pilot-digital-currency-seeking-leverage-financial-services-2023-03-06/.

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analyze trends in cryptocurrency investments and the perceptions of this technology among the population to prepare for significant social and economic changes brought about by technological developments in decentralized finance.

Cryptocurrency research is extensive and spans from the technological characteristics of digital assets and blockchain technology to cryptocurrency adoption's social and environmental impacts. In the finance literature, the behavior of cryptocurrency markets has quickly become one of the central topics in alternative investments [6–8]. However, the existing evidence is highly based on analysis of financial data, media, and online trends [9]. These findings do not offer sufficient insights into the motives of cryptocurrency ownership, sociodemographic characteristics of investors, and other qualitative factors that might help to forecast technology adoption trends. Another significant focus in the literature revolves around the psychological traits of individuals and their impact on intentions to invest in cryptocurrency [10, 11]. Specifically, recent findings indicate that individuals with higher levels of narcissistic admiration tend to demonstrate positive attitudes towards cryptocurrencies [12].

Research on the profile, socioeconomic drivers, and attitudes of users or investors in the cryp-tocurrency ecosystem remains relatively scarce and highly concentrated in developed countries (e.g., Refs. [13–16]. Further evidence is available from surveys conducted by the Financial Conduct Authority (e.g. Ref. [17], companies' reports (e.g. Ref. [18], and global crypto-asset benchmarking studies (e.g., Ref. [19]. Such investigations are focused on the characteristics and behavior of the average cryptocurrency investor or user. For example, in Germany [9], finds evidence that cryptocurrency investors hold high-risk portfolios, rotate their positions a lot, and are more likely to incur behavioral biases than other investors. Similarly, based on a sample of 20,385 investors from the exchange CryptEx [20], find that cryptocurrency investors show significant heterogeneity in performance, with little evidence of higher returns over time [21]. analyze cryptocurrency in-vestment intentions, applying a fuzzy analytical framework, social support theory, and financial literacy. Social Influence emerges as the most influential factor, with specific priorities including financial knowledge, social influence, and resource availability. In addition to behavioral and port-folio characteristics [15], finds that the average Japanese crypto asset owner is young and male, and has a higher level of financial literacy relative to noncrypto asset owners. Very similarly [22], show that males, younger adults, and the more educated are more likely to engage in the cryptocurrency market. Corroborating earlier findings [23], find that investors more risk-tolerant, young adults, and males are more likely to adopt cryptocurrency in Austria. Furthermore, the authors find a strong association between investors' ESG preferences and crypto-investment exposure.

There are only a few studies available to date based on detailed, single-entity datasets or comprehensive surveys in emerging countries. For example [24], explored the perception of Bitcoin adoption in South Africa, and found that the complex nature and high price volatility of bitcoin are key barriers to adoption. In China [25], found that perceived usefulness and trustworthiness are predictors of bitcoin usage [26]. explored the influence of financial and behavioral factors on investment decisions in the Gulf Cooperation Council (GCC) cryptocurrency market, finding that herding, prospect, and heuristics theories collectively can explain investors' decisions during extreme market conditions in Bahrain, Saudi Arabia, Kuwait, and the UAE. Meanwhile [27], examined the motivations of Malaysian retail investors in cryptocurrency investment, discovering that factors like compatibility, trialability, ease of use, observability, and perceived value significantly influence investment intentions. To our knowledge, there are no similar studies to ours that have been conducted in Brazil, even though the country ranks #9 in the Chainalysis 2023 Global Crypto Adoption Index[3] and digital currencies have gained broad support among retail investors in the country.[4]

Regarding the specific factors that attract and repel investors in the crypto ecosystem, and how attitudes vary among different cryptocurrency investors, evidence is currently scarce [28]. find that high volatility of the asset class does not lower institutional investors' confidence as long as the market can offer accurate and timely information on prices to meet investors' price consciousness. Such conclusions are drawn from a sample of 253 multinational PE company investment managers who have bought and used cryptocurrency. In addition to institutional managers' perception, some work has also been done with retail investors [29]: find that younger individuals with lower income and education and late investors are more optimistic about the future value of cryptocurrencies, and [16] find that cryptocurrency investors are not motivated by distrust in fiat currencies or regulated finance. Additionally [9], find that cryptocurrency investors are more likely to follow a "trend-chasing behavior" and other aspects of technical analysis. In emerging markets, however, cryptocurrency research on beliefs and heterogeneity among cryptocurrency investors (e.g., early and late adopters, young and mature investors, males and females, and sophisticated and unsophisticated) is under-explored.

One natural reason for the lack of great extent of research is the anonymous nature of crypto investments - investors can trade cryptocurrency without having a direct, traceable link to a bank or investment account. Furthermore, the application of questionnaires to groups on social networks composed of crypto market enthusiasts is methodology problematic since the selection bias of respondents (who self-select) tends to be very high. The consequence of this problem is the low reliability of the search results [30]. A third potential reason is that there is less available data on emerging relative to developed economies, which may explain why the literature has focused on developed countries [31] despite the fact that cryptocurrency adoption is biased toward emerging or less developed economies.[5]

To overcome these barriers and mitigate the influence of selection bias on the results, our methodological strategy consists of sending a proprietary questionnaire through five partner in-vestment offices in Brazil, whose clients are all online investors (our target population). These offices are among the largest in the country (three are in the top 10 investment offices of XP, Inc., the leading digital financial company in Brazil) and offer a wide range of financial services and investment opportunities, both related and unrelated to cryptocurrency. Thus, because some of the investors have cryptocurrencies in their portfolios and some of them do not, we can compare crypto and non-crypto investors to tackle the research questions that have not been addressed before. With such an empirical strategy, which is consistent with [32]; the scope of the respondents' profile is delimited to investors only, including cryptocurrency investors and investors who have never invested in crypto-assets. The latter group is of fundamental importance when it comes to comparing investors who have and those who do not have crypto-assets in their portfolios for examining the barriers to cryptocurrency adoptions. Our sample totals 573 Brazilian online investors, of which 410 are non-crypto (≈71.6%) and 163 are crypto holders (≈28.4%). We received all responses between February and March 2021.

Using univariate and multivariate econometric analyses, the results suggest that crypto in-vestors are, on average, younger, more tolerant to risk, less optimistic regarding the real economy, and more likely to be male than non-crypto investors. Contrasting these sharp differences in

[3] https://www.chainalysis.com/blog/2023-global-crypto-adoption-index/.

[4] A typical retail investor in Brazil accesses cryptocurrency through a national or international exchange or, since May 2021, through spot ETFs that have been extensively adopted in the country [65].

[5] In the Chainalysis' 2022 Global Crypto Adoption Index, the top 15 countries are almost all considered emerging or less developed countries: Vietnam, Philippines, Ukraine, India, USA, Pakistan, Brazil, Thailand, Russia, China, Nigeria, Turkey, Argentina, Marocco, and Colombia, in this particular order.

in-vestor behavior and characteristics, we find that crypto and non-crypto investors are similar in terms of educational background in finance or related areas. Interestingly, predictors of crypto investment seem to vary across age groups. For younger investors (up to 39 years old), gender and risk tolerance are robust determinants of cryptocurrency investment. In the middle part of the age distribution (40–59y), risk tolerance and optimism with the real economy dominate. Finally, in the elderly group (60+), the only systematic predictor of crypto investment is gender (females are less likely to invest). This potential gender gap in cryptocurrency investment even after controlling for risk attitude, educational background, and self-perceived performance is consistent with recent evidence on a gender gap in the access to fintech services [33].

Further heterogeneity analyses also show that not all cryptocurrency investors are created equal: late investors are more likely to be attracted by past returns and low-interest rates than early adopters. Meanwhile, the key distinction between young and experienced investors' beliefs is that the former group is attracted by popularity and uncorrelation with the real economy. Critical differences between unsophisticated (more likely to invest because of past returns) and sophisticated and males (more confident in the long run potential of DLT technology) and females are also found. Mapping such heterogeneity among cryptocurrency investors is vital to understand the complexity of this growing ecosystem and designing effective regulations to spur financial innovations while protecting users.

Our contributions to the literature are threefold. First, we map the profile of crypto investors through an empirical strategy that mitigates impacts arising from selection bias and goes beyond pure administrative, single-entity data. As [34] notes, survey data appears increasingly useful for learning about beliefs. Second, by identifying key differences and similarities between crypto and non-crypto investors as well as heterogeneity in their beliefs in a country of large crypto adoption but academically under-investigated, we expand a growing literature on the characteristics and behavior of crypto investors [9,12,16,20,28,29,35,36]. Third, and most importantly, to our knowledge this is the first paper to dissect the attracting reasons to adopt cryptocurrencies among different investor groups (early vs late adopters, sophisticated vs unsophisticated, young vs experienced, and males vs females), which is critical to understand the complexity of cryptocurrency adoption. Such findings are vital for policy-makers and regulators to design wider adoption of digital assets in the era of CBDCs and tokenized economies.

Finally, one should note that our paper differentiates from previous surveys on the topic for two main reasons. First, it was conceived specifically for this research project and is likely to be one of the most embracing and in-depth surveys to understand the topic. To get information on relevant, real-world issues in the cryptocurrency ecosystem, the portfolio manager and a director from the largest digital asset management firm in Latin America actively participated in the conception, criticism, and validation of the questionnaire. Thus, we should think of our survey as a joint effort between academics and practitioners. Second, to the best of our knowledge, this is the first academic paper that uses data from a survey on an emerging market that clearly delimits its target population and reduces sampling and non-sampling survey errors through partnering with country-leading digital investment offices that offers both crypto and non-crypto-related services to clients that are diverse on the socioeconomic and geographic dimensions.

The remainder of the article is organized as follows: Section 2 discusses the background litera-ture. Section 3 describes the methodological procedures and discusses the sample characteristics. Section 4 presents and discusses the results of the empirical analyses. Finally, Section 5 concludes.

2. Theory development

The theories surrounding the adoption of new technologies are extensive. In financial research, the intentions to invest in cryptocurrencies are frequently elucidated through the lenses of financial market participation and behavioral finance theories. Investors may be driven by a combination of rational and irrational motives when deciding to invest in cryptocurrencies. Rational motives are primarily linked to the risk-return profiles of crypto assets. The abnormal returns offered by cryptocurrencies and the technological attributes of these novel investment assets can be attributed to rational factors. However, the high volatility, cybersecurity risks, and the speculative nature of cryptocurrency markets lead us to believe that irrational and behavioral factors may exert a more prominent influence on the decision-making process for cryptocurrency investments.

Behavioral factors, such as gender and overconfidence, have been identified as influential in cryptocurrency adoption. While cryptocurrency is a relatively new investment asset, valuable in-sights can be gleaned from early literature on market participation and the intentions of holding risky assets in investment portfolios. Research indicates that men tend to hold riskier portfolios than women, attributed to disparities in confidence levels and investment knowledge [37]. Moreover [38], demonstrated the significant influence of demographic and psychological factors, including age, education, income, trust, risk aversion, and financial literacy, on stock market participation. Financial literacy has also emerged as a key determinant of risky investment, with studies illustrating its positive association with holding stocks and other high-risk assets [39,40]. Recent research by Ref. [41] suggests a positive relationship between societal trust and cryptocurrency adoption. Acknowledging the potential for non-rational decision-making, this study hypothesizes that a combination of psychological, demographic, and financial literacy factors may explain cryptocurrency investment decisions.

From psychology perspective, recent research conducted by Ref. [11] delved into the motivations of individuals exhibiting Dark Tetrad traits, such as Machiavellianism, narcissism, psychopathy, and sadism, in their interest in cryptocurrencies. Their findings revealed that narcis-sism positively influenced crypto attitudes, mediated by positivity, while Machiavellianism affected buying intentions through the mediation of conspiracy beliefs. Moreover, the study uncovered how psychopathy impacted crypto judgments via the fear of missing out (FoMO) and a decrease in positivity, whereas sadism was associated with FoMO and diminished positivity, both influencing crypto judgments.

In a separate study [12], explored the link between individual characteris-tics and attitudes towards cryptocurrencies and traditional investments. The research highlighted that individuals with higher levels of narcissistic admiration exhibited positive attitudes towards cryptocurrencies, while those with narcissistic rivalry showed a negative association. Additionally, financial literacy emerged as a significant predictor of attitudes towards traditional stock investments, while intelligence was inversely associated with attitudes towards cryptocurrencies. This suggests that narcissism, particularly in the form of admiration, may play a critical role in shaping positive attitudes towards cryptocurrencies, with intelligence potentially influencing a more cautious approach.

Recent research by Ref. [10] has shed light on the influence of trait reactance and messages regarding freedom-protecting versus freedom-restricting crypto regulations on individuals' attitudes and buying intentions towards cryptocurrency. Examining the mediating effects of positive and negative affect, their study encompassed 566 participants in a design evaluating trait reactance and regulation content. The findings emphasized that trait reactance positively influenced state reactance and positive affect, subsequently affecting crypto buying intentions through the mediation of positive affect and anger. Moreover, the study revealed that freedom-oriented messages led to heightened positive affect and reduced anger, indicating that messages promoting freedom in crypto investments elicited a more favorable response compared to those outlining restrictions.

To comprehend the dynamic landscape of digital consumption and ownership [42], highlight the dramatic transformation of money, possessions, and ownership within the evolving realm of the Metaverse. They explore the impact of cryptocurrencies, algorithmic collectibles, and NFTs, aiming to unravel the intricacies of disintermediation through online auctions and specula-tion. Notably, they emphasize the emergence of new ownership models like fractional ownership and fractionalized property rights. Additionally, the authors delve into the motivations behind the exorbitant prices paid for seemingly simplistic digital artwork with limited property rights, underscoring the diverse buyer motivations prevalent in the crypto art sphere. Their insights offer practical implications for artists, art institutions, buyers, and investors, while also forecasting the potential implications of these trends as society transitions toward the Metaverse. In contrast [43], challenge the conventional notion that firms are the sole market-shaping actors. Drawing from an ethnographic study of cryptocurrency communities, they elucidate four distinct roles played by individuals in shaping cryptocurrency markets, accompanied by a delin-eation of six micro-level market actions. This nuanced typology and theoretical model contribute to a deeper understanding of how these actions influence market size, offerings, and functioning. Their work establishes a critical foundation for future research and provides managerial guidelines for practitioners navigating the complexities of cryptocurrency markets.

[44] shed light on the influential role of vloggers in shaping audience perceptions within the blockchain, crypto-assets, and Web3 industry. Their analysis of sentiment across various YouTube Bitcoin vlogs reveals a significant emotional contagion effect, particularly concerning negative emotions. Additionally, they highlight the gender imbalance within the influencer sphere and the consistent emotional influence maintained by vloggers over time. Their findings underscore the implications for marketers operating within blockchain-based markets, as well as the need for regulatory awareness regarding the impact of crypto vloggers on the broader financial landscape. In the realm of Initial Coin Offerings (ICOs) [45], investigate the signaling effects of Corporate Social Responsibility (CSR) narratives on ICO outcomes. By analyzing a global sample of ICOs, they demonstrate that socially responsible ICOs tend to reflect values aligned with broader stakeholder interests, thus reducing information asymmetry and improving fundraising prospects. Moreover, they identify cultural influences on the adoption of CSR, showcasing how ICOs from countries with a strong emphasis on collective values are more inclined towards socially responsible goals. Their insights offer valuable guidance for entrepreneurial ventures on establishing legitimacy and for investors on evaluating signals in the volatile private equity markets. Finally [46], address concerns regarding the valuation of bitcoin, particularly in light of celebrity and government endorsements. Through the application of Cue Utilization Theory and Signaling Theory, they reveal a significant association between positive celebrity tweets, favorable government sentiments, and upward shifts in bitcoin prices. Their findings caution investors about the transient nature of price fluctuations triggered by celebrity endorsements, emphasizing the importance of diversified portfolios in managing risk.

Cryptocurrency adoption has garnered significant attention within the digital market, as evidenced by recent empirical studies. [47] present a comprehensive analysis of the factors influencing the adoption of cryptocurrencies in Malaysia. Their research underscores the pivotal roles of social influence, transparency, price value, traceability, and attitude in shaping customer satisfaction, which in turn mediates the adoption process. While several factors positively impact adoption, traceability emerges as a detracting force within the Malaysian digital market. The findings provide valuable insights for researchers exploring the dynamics of cryptocurrency adoption in various regions, emphasizing the need to understand the nuanced influences on this emerging market. In a related context [48], investigate the impact of trust on citizen behavior in the context of blockchain-based cryptocurrencies, focusing on the Mano River Union sub-region. Their quantitative analysis emphasizes the significance of technology at-tachment, blockchain transparency, and trust in shaping citizen behavior toward cryptocurrency adoption. However, the moderation effects of ethical issues introduce complexities, suggesting the necessity of an inclusive approach in the development of blockchain technology. The study advocates for a holistic understanding of the interplay between technology, trust, and ethical con-siderations to ensure a seamless integration of cryptocurrencies within the Mano River Union and beyond. Meanwhile [49], delve into the priorities of drivers for investing in cryptocurrencies, employing the Fuzzy Full Consistency Method-Bonferroni (FUCOM-F'B) model.

By classifying twenty-three drivers into categories such as functionality, financial, legal infrastruc-ture, technology, and security, the study identifies "strong electronic encryption" and "use of digital signature" as the foremost determinants for preferring a cryptocurrency. The proposed approach accounts for the complexities and subjectivity inherent in decision-making processes, serving as a valuable decision support tool for regulators, policymakers, practitioners, and cryptocurrency investors seeking to navigate the multifaceted landscape of crypto investments.

[25] explored the adoption of cryptocurrencies, particularly Bitcoin, within mainland China. Their inquiry reveals that awareness and perceived trustworthiness play pivotal roles in shaping the intention to use Bitcoin, with perceived usefulness acting as a partial mediator between perceived ease of use and intention to use. By delineating the factors influencing Bitcoin adoption in China, the study not only contributes to existing theories of adoption but also provides valuable insights for policymakers seeking to understand the dynamics of cryptocurrency adoption within diverse global contexts [26]. conducted a study to explore the influence of financial and behavioral factors on investment decisions within the Gulf Cooperation Council (GCC) cryptocurrency market. Using a cross-sectional absolute deviation methodology, the study examined herding behavior during extreme market conditions in Bahrain, Saudi Arabia, Kuwait, and the UAE. Findings revealed that herding theory, prospect theory, and heuristics theory collectively explain 16.5% of the variance in investors' decisions. [27] examined the motivations of Malaysian retail investors to engage in cryptocurrency investment amidst the country's digitalization initiatives and growing concerns about fraud. Their integrated model, combining diffusion of innovation theory and consumer behavior theory, revealed the significant influence of compatibility, trialability, ease of use, observability, and perceived value on investment intentions. However, the study did not find support for the impact of relative advantage and perceived risk.

The behavioral cryptocurrency literature is extensive, encompassing various studies [5,6,44]. However, there is limited evidence available to date on intentions to invest in cryptocurrency among Brazilian digital investors. To address this gap, our paper aims to contribute to the existing knowledge by providing a comprehensive un-derstanding of the primary motivations and barriers faced by Brazilian digital investors in their cryptocurrency investments, adding to the prior wrok of [12,21, 41]; to name but a few. Motivated by the papers discussed earlier that employed survey methods to capture attitudes toward investing in cryptocurrency in emerging markets, we also selected the survey method for our study in Brazil. By comparing the behaviors of crypto and non-crypto investors, this study elucidates distinctive factors that increase the likelihood of includ-ing cryptocurrencies in an investment portfolio. In doing so, our research enhances the broader understanding of investor behavior in the context of the rapidly evolving cryptocurrency market.

3. Methodological aspects

The research methodology is based on the elaboration, validation, and application of a proprietary survey, whose target audience is composed of Brazilian digital platform investors. There are several important methodological aspects regarding internal validity (degree of reliability) and external validity (generalization and extrapolation) of the results that we discuss in detail.

3.1. Survey design, biases mitigation, and sample size

One of the critical challenges of the survey methodology concerns selection bias. More generally, total survey errors are a sum of sampling error and non-sampling errors [30,50]. The former is induced by sampling design and is higher when the sample is small relative to the population. Thus, one may limit sampling errors (estimation plus specification errors) by surveying a representative sample of the target population. The latter occurs even when the sample equals the population: it arises from both observation (over-coverage, measurement error, and processing error) and non-observation errors (under-coverage error and non-response error).

To overcome such barriers and mitigate the influence of biases on the results, we send the questionnaires through five Brazilian investment offices that collaborate with this research. These offices are among the largest in Brazil – the 1st, 3rd, and 5th largest offices in AUM at XP, Inc., the leading digital investment management firm in Brazil, are present in our sample – see Ref. [51] –, having a large number of clients in virtually all geographic regions in the country.[6] Thus, those that received the e-mail invitation to participate in the survey are all digital platform investors (our target audience). Throughout their investment accounts, they can hold a wide range of financial instruments: fixed income, equities, investment funds (exposure to commodities, cryptocurrencies, VC/PE, etc.), and private pension funds, among others. Next, we discuss how the chosen survey design mitigates sampling and non-sampling errors and the limitations of such a strategy.

Sampling error. Sampling error may arise from both estimation and specification errors (Beth-lehem, 2010). The former consists of the fact that every new selection of survey elements will result in different samples, thus different inferences on the population. The latter occurs when the selection probabilities in the sample design differs from the selection probability in the popu-lation. Both converge to zero when the observed sample equals the complete population. In our particular design, we reduce sampling errors by strategically partnering with some of the largest digital investment offices in Brazil, whose clients, summed, are likely to be representative of the population of digital investors in the country.

It is essential to clarify a common misconception that a higher number of respondents increases representatives and, thus, could arguably reduce sampling error. We could have chosen a naive strategy of simply putting the questionnaire on the web, allowing elements outside our target population to participate in the survey (by self-selecting themselves) and increasing the number of respondents. However, as [30] notes, in these so-called "self-selection surveys" the researcher loses control of the selection process,[7], and no clear target population can be defined. Therefore, one can not compute unbiased estimates, despite the sample size. That is the key reason why we use a survey strategy that takes advantage of sizeable digital investment offices.

Non-sampling error. The first non-sample error we try to control in our survey design is over-coverage. As previously mentioned, instead of a naive strategy of simply putting the questionnaire on the web, we minimize the over-coverage error by delimiting our target population (Brazilian digital platform investors) and inviting only them to participate in the survey. Since only online investors with an active account at one of our partnering investment offices were able to answer the questionnaire, we minimize the number of survey respondents that do not belong to the target population.[8]

A second concern on non-sampling errors that we try to overcome is measurement error. Be- fore finishing the questionnaire, we proceeded to two rounds of evaluation of content validity with colleagues in academia, industry, and a small sample of individuals that belong to the target pop-ulation (Brazilian digital investors). Written and spoken feedback were important to improve the clarity of language and the practical pertinence of questions in our survey, thus limiting measurement error. Of course, despite our methodological efforts, there are sources of measurement errors that can not be avoided – for example, some respondents may not report their true beliefs.

We also seek to mitigate two additional sources of non-sampling survey errors – under-coverage and non-response. Specifically, we alleviate the under-coverage error (a type of non-sampling, non-observation error) because we set our target population to online platform investors, who nec-essarily have an internet connection. Thus, our target population does not exceed the population with access to the Internet, and no under-coverage is likely to occur.[9] However, as [52] alert, some participants may never receive the invitation to participate because the invitation is intercepted (e.g., spam filter) before they see it. Regarding the non-response error, we try to let the survey as direct and concise as possible to avoid a situation where the investor clicks on the link but fails to provide complete answers to the questionnaire. It is also important to note that we rely on other good practices in the survey (see, for example [53], methodology – techniques ranging from the elaboration of the questionnaire in direct and "friendly" language, randomization of the order of each answer alternative, to the initial clear e-mail message containing the *deadline* [53]. To increase the response rate, our partnering offices also send a reminder e-mail days before the deadline for completion. Finally, but not less importantly, the Ethics Committee of our university has approved the questionnaire,[10], and all participants electronically consented to participate voluntarily in this research.

Summary of advantages and disadvantages. Despite the natural limitations of surveys and the fact that we could have a larger number of responses with alternative sampling strategies (e.g., "self-selection surveys"), we have several benefits of choosing our survey design. First, the scope of the respondents' profile (digital investors only) is delimited, thus minimizing over-coverage error. Second, since the partnering investment offices are among the largest ones in the country, the sample frame approximates to the population frame. Third, having several partners reduce the influence of the idiosyncratic component of each investment firm (e.g., income profile, geographical concentration, age, among others). Fourth, since those clients are able to invest in a far-reaching range of financial instruments, including cryptocurrency products, we are able to generate a sub-sample of investors that hold cryptocurrency in their portfolios (directly or indirectly) and a sub-sample of respondents that do not hold cryptocurrency. The latter group is of fundamental importance when it comes to comparing the sociodemographic, behavioral, and beliefs of investors who have and those who do not have crypto assets in their portfolios.

As limitations to our approach, given that participation in the survey

[6] The five partners are part of either XP Inc. or BTG, the two leading investment management companies in Brazil, that offer extensive financial services and investing solutions.

[7] Those that respond are those that happen to see the link and decide to click and participate in the survey.Thus, it ends up in a self-selected sample without a clear delimited population target.

[8] We can not say that we set the over-coverage error to zero because nothing prevents a participant to forward the link to participate to non-clients. However, since the invitation to participate in the survey was directly sent by the partnering investment office with very specific information, it is unlikely that it is a significant concern in our setting.

[9] [30] refers to "under-coverage bias" as the type of bias that arises from the fact that just the internet population may answer web-based surveys and not the complete target population. In our particular setting, every element in the target population has access to the internet.

[10] University Ethic Committee, opinion no. 252/2020, December 16, 2020.

Table 1
Bias reduction in the proportion of crypto investors in the sample.

	Sample #1: 5 partnering investment offices	Sample #2: Hashdex's clients and social media followers
# of respondents	573	229
Respondents that have already invested in cryptocurrencies	163	179
Respondents that have never invested in cryptocurrencies	410	50
Proportion of crypto investors	28.4%	78.2%
Proportion of non-crypto investors	71.6%	21.8%

Note: This table presents the representativeness of crypto investors within our methodological approach to reduce self-selection bias (sample #1: five partnering investment offices) and within an alternative, likely to be biased sample (sample #2: Hashdex's clients and social media followers). If our methodological strategy effectively reduces the bias toward crypto investors, we may expect the ratio of crypto investors to be significantly lower in sample #1 (left column).

is voluntary, individuals who have a greater affinity or interest in the cryptocurrency market are more likely to click and respond to the survey. Thus, despite reducing self-selection bias relative to pure internet-based surveys, we expect the fraction of crypto investors on the total sample of investors to be overstated relative to the population. However, because our objective in this research is *not* to quantity the number or the fraction of crypto investors among digital investors but rather to compare their characteristics and beliefs, it is unlikely to be a significant concern. Furthermore, as we show later in an experiment, our strategy significantly reduces the self-selection bias.

Sample size and reduction of self-selection bias. As a result, we received responses from 573 Brazilian digital investors from February to March 2021, of which 410 are non-cryptocurrency (71.6%) and 163 are cryptocurrency investors (28.4%). All responses were collected throughout the SurveyMonkey platform. To analyze whether the self-selection bias reduction strategy is effec-tive, we carry out the following experiment. We complement the application of the questionnaire based on the five partnering investment offices by sending the same questionnaire through Hashdex, a digital asset management firm that is also a supporter of this project. Unlike the former clients, Hashdex's clients and social media followers have a natural predisposition to invest in cryptocur-rencies – a sample that is probably much more biased than that from our methodological strategy. To test this hypothesis, we analyze the percentage of respondents in each sample (5 investment offices vs Hashdex) that have already invested in crypto assets. If our strategy is really effective in reducing the self-selection biases discussed

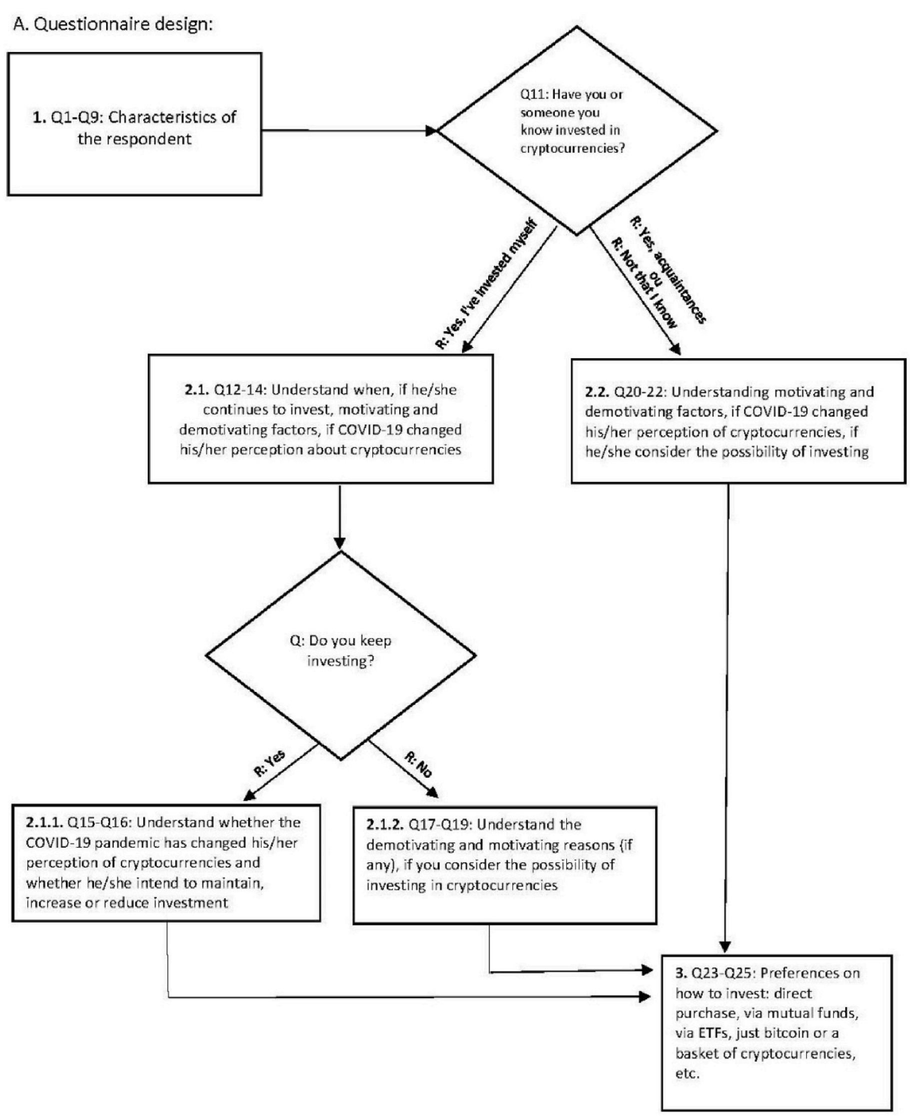

Fig. 1. Design and content of the questionnaire.

above, the former sample should have a much lower proportion of respondents who said they had invested in crypto than the Hashdex sample. The Table below presents the result of such an experiment to validate the sample identification strategy. We got 229 responses at the Hashdex sample from May to June 2021.

To evaluate if our strategy was effective to reduce self-selection bias, we send the exact same questionnaire to Hashdex Asset Management Ltd., a digital asset management firm whose clients and social media followers are far more likely to be crypto enthusiasts than the typical investor. We hypothesize that the ratio of crypto investors in this particular sample is far greater than the ratio of crypto investors in the sample obtained with the 5 partnering offices.

As Table 1 shows, in the sample considered biased (Hashdex), which would be a naive strategy for building the sample, the proportion of crypto investors in the sample is (179/229 =) 78.2%. In the sample resulting from our methodological strategy to reduce bias towards crypto investors (of-fices that offer investments in crypto assets and investments in other asset classes), this proportion is inverted: only (163/410 =) 28.4% of the respondents said they have invested in cryptocurrencies. The latter is believed to be a measure much closer to the true number than the former. Therefore, we argue that the selection bias mitigation strategy proposed here results in an effectively different sample, less biased in relation to the one that would be obtained with a naive strategy.

Despite the effort to reduce self-selection and the biases resulting from it, we emphasize that it is not possible to eliminate it completely. Investors more interested in crypto-assets will naturally be more likely to respond to the survey than investors who are not interested in this market, despite the strategy of focusing the survey on Brazilian investors in digital platforms.

3.2. Questionnaire characteristics and ramifications

We constructed an initial survey instrument based on existing research (e.g. Refs. [18,54], and jointly with two practitioners – the portfolio manager and one partner of the leading digital asset management firm in Latin America. We then solicited feedback from some academics and practitioners and refined the survey accordingly. A critical distinction from previous research (e.g. Refs. [15,16], is that our questionnaire was designed specifically for this research project, and thus we were able to have more depth in questions. The consent form and all the following questions and alternatives are shown in the Online Appendix A.1. The document has three parts, as shown in Fig. 1. The first (P1) seeks to understand the general characteristics – age, gender, financial education – and behavioral traits of the respondent – risk profile and sentiment on prospects of the real economy (similar to, e.g., Ref. [54]. The second (P2) seeks to understand the respondent's perceptions and motivations to-wards cryptocurrency, taking into account a ramification: if the participant reveals that he has already invested in cryptocurrencies, he is taken to part 2.1 (focus on understanding reasons to invest, when the first investment occurred, if he/she intends to maintain, increase or reduce crypto exposition, among others); otherwise 2.2. In 2.2., specific questions are made for those that have reported never invested in cryptocurrency: demotivating factors, if he/she considers the possibility of investing in cryptocurrency, etc.). The third part (P3) is common to both groups and seeks to understand preferences on investing in crypto assets – whether through mutual funds, direct purchase throughout exchanges, ETFs, investing in bitcoin only, or in a basket of cryptocurrencies, etc.

3.3. Regression specification and variables

In addition to standard tests to compare the (unconditional) differences between respondents who invest in crypto assets and those who invest only in other financial instruments (Pearson's chi-squared test for categorical variables), the following regression model is proposed to identify the effect of each predictor on the dependent variable (similarly with, e.g. Ref. [32],:

$$Y_{ij} = \alpha_0 + \Sigma_k \beta_k X_{kij} + \lambda_j + \epsilon_{ij} \tag{1}$$

where Y_{ij} is an outcome of the survey (for example, a dummy variable equal to one if he/she has already invested in cryptocurrency, and zero otherwise – Question 11, or the propensity to invest an unexpected, additional income in crypto assets – Question 7, or motivating reasons to invest – Question 13 of the questionnaire) for investor i at investment office j. X_{kij} is a vector of control variables (Age, Gender, Real Economy Optimism, Risk Tolerance, Financial Education Background, Perceived Investment Performance), λ_j are investment office fixed effects[11], and ϵ_{ij} is the idiosyncratic error term. The coefficients β_k measure the impact of each predictor on the outcome of interest, and the reported standard errors are robust to heteroscedasticity. Since we have a binary dependent variable, we estimate Eq. (1) using a logistic model.[12]

The core control variables used in the regressions are measured as follows. *Age* is a categorical variable extracted from Question 1, whose values range from one to six (where 1 refers to "Less than 20 years" and 6 to "60 years or more". *Female* is a binary variable equaling one for female respondents (Question 2). *Real Economy Optimism* is a categorical variable that equals one, two, and three for pessimist, neutral, and optimist expectations on the Brazilian economy, respectively (Question 3).[13] *Risk Tolerance* is a categorical variable ranging from one (conservative) to four (aggressive risk profile) and extracted from a suitability test (Question 4). *Financial Education Background* refers to Question 5 and ranges from 1 ("Not familiar with") to 4 ("B.Sc., B.A., M.Sc. or Ph.D. in finance or related areas"). *Perceived Investment Performance* is a categorical variable representing a self-evaluation of investment performance on a 0 to 10 scale (Question 8). After qualitative and quantitative analyses based on [55,56]; the categorical, ordered independent variables (*Real Economy Optimism*, *Risk Tol-erance*, *Financial Education Background*, and *Perceived Investment Performance*) were treated as continuous in the regressions.[14]

We also perform additional analyses. Particularly, to gauge potential differences in the predic-tors at different age groups (whose behavior might differ), we further estimate Eq. (1) conditional on the following age groups: up to 29 years, 30–39 years, 40–49 years, 50–59 years, and 60+ years. By doing that, we can analyze if and how the relative importance of each predictor differs across age groups. In addition, to evaluate the underlying socioeconomic differences and similarities between investing a marginal, unexpected income in cryptocurrency

[11] Investment office fixed effects aim to absorb any systematic differences among investors at different investment companies that might relate to the likelihood of investing in cryptocurrencies (e.g., investment offices might target investors with different geographical, cultural, and socioeconomic characteristics). Our results are nearly the same if we exclude these controls.

[12] Using techniques like OLS regression in this setting would lead to misleading estimates of independent variable effects and inappropriate hypotheses tests [55]. Furthermore, the logistic regression also corroborates past research on the topic [9].

[13] Answers "I don't know how to answer" were treated as Neutral expectations. It happened 19 times among the 573 responses.

[14] As [56] state, the advantage of treating ordered categorical variables as continuous is that interpretation is simpler, and it makes sense as long as successive categories of the ordinal independent variable are equally spaced. In our setting, it seems plausible, for example, that the distances from "Pessimist" to "Neutral" and from "Neutral" to "Optimist" are comparable. Furthermore, following [55]; we perform three tests (Likelihood Ratio Chi-Square, BIC, and AIC) comparing an unconstrained model that treats ordinal variables as continuous to a constrained model that treats those variables as categorical. All three tests confirm that treating those ordinal variables as continuous in the regressions is preferable. However, as a robustness check, we have rerun our empirical analyses considering those variables as categorical, and the findings are largely unchanged.

Table 2
Descriptive statistics across groups of respondents.

Factor	(A) Full sample	(B) Non-crypto investors	(C) Crypto investors	(B–C)
N	573	410	163	
Age				< 0.001
< 20y	4 (0.7%)	2 (0.5%)	2 (1.2%)	
20-29y	30 (5.2%)	14 (3.4%)	16 (9.8%)	
30-39y	156 (27.2%)	100 (24.4%)	56 (34.4%)	
40-49y	126 (22.0%)	90 (22.0%)	36 (22.1%)	
50-59y	114 (19.9%)	87 (21.2%)	27 (16.6%)	
>60y	143 (25.0%)	117 (28.5%)	26 (16.0%)	
Female	127 (22.2%)	108 (26.3%)	19 (11.7%)	< 0.001
Real Econ. Optimism				0.13
Pessimist	188 (32.8%)	128 (31.2%)	60 (36.8%)	
Neutral	191 (33.3%)	133 (32.4%)	58 (35.6%)	
Optimist	194 (33.9%)	149 (36.3%)	45 (27.6%)	
Risk Tolerance				< 0.001
Conservative	40 (7.0%)	34 (8.3%)	6 (3.7%)	
Moderately Conservative	190 (33.2%)	160 (39.0%)	30 (18.4%)	
Moderately Aggressive	208 (36.3%)	141 (34.4%)	67 (41.1%)	
Aggressive	135 (23.6%)	75 (18.3%)	60 (36.8%)	
Educ. Background				0.005
Not familiar with	53 (9.2%)	48 (11.7%)	5 (3.1%)	
Self-learning	318 (55.5%)	228 (55.6%)	90 (55.2%)	
Other courses in finance or related areas	85 (14.8%)	59 (14.4%)	26 (16.0%)	
B.Sc./B.A., M.Sc. or Ph.D. in finance or related areas	117 (20.4%)	75 (18.3%)	42 (25.8%)	
Perceived investment performance				0.012
0	6 (1.0%)	6 (1.5%)	0 (0.0%)	
1	2 (0.3%)	1 (0.2%)	1 (0.6%)	
2	4 (0.7%)	3 (0.7%)	1 (0.6%)	
3	18 (3.1%)	17 (4.1%)	1 (0.6%)	
4	24 (4.2%)	21 (5.1%)	3 (1.8%)	
5	109 (19.0%)	83 (20.2%)	26 (16.0%)	
6	83 (14.5%)	64 (15.6%)	19 (11.7%)	
7	182 (31.8%)	128 (31.2%)	54 (33.1%)	
8	117 (20.4%)	70 (17.1%)	47 (28.8%)	
9	19 (3.3%)	12 (2.9%)	7 (4.3%)	
10	9 (1.6%)	5 (1.2%)	4 (2.5%)	
Portfolio allocation of an unexpected income				< 0.001
No crypto	413 (72.1%)	350 (85.4%)	63 (38.7%)	
Some crypto	134 (23.4%)	49 (12.0%)	85 (52.1%)	
100% crypto	26 (4.5%)	11 (2.7%)	15 (9.2%)	
Cryptocurrency financial literacy				< 0.001
All incorrect	69 (12.0%)	66 (16.1%)	3 (1.8%)	
1/3 correct	257 (44.9%)	234 (57.1%)	23 (14.1%)	
2/3 correct	154 (26.9%)	93 (22.7%)	61 (37.4%)	
All correct	93 (16.2%)	17 (4.1%)	76 (46.6%)	

Table 2 (*continued*)

Factor	(A) Full sample	(B) Non-crypto investors	(C) Crypto investors	(B–C)
Type I error	480 (83.8%)	393 (95.9%)	87 (53.4%)	< 0.001
Type II error	91 (15.9%)	80 (19.5%)	11 (6.7%)	< 0.001

Note: This table presents the descriptive statistics of the core variables used throughout the paper. The p-values of the last column refers to the Pearson's chi-squared test difference between non-cryptocurrency (Panel B) and crypto-currency investors (Panel C). The null hypothesis states that both groups (Non-crypto and Crypto investors) are equal. The number of respondents in the Full Sample (Panel A) is 573; in the Non-Crypto Investors subsample (Panel B), 410; in the Crypto Investors subsample (Panel C), 163. For each variable, we show the absolute number and the relative importance of each value (%, in parenthesis).

versus other finan-cial instruments (fixed income, FX, commodities, stocks, etc.), we perform a stratified analysis in section 4.3. Finally, in section 4.4, we incorporate as independent variables proxies for cryptocur-rency financial literacy and investor sophistication, which refers to Question 9 and Question 8, respectively. Details are given in that section.

3.4. *Descriptive statistics and univariate analysis*

We begin our analysis by analyzing the descriptive statistics of each explanatory variable for the full sample (N = 573, Panel A), Non-Crypto Investors (N = 410, Panel B), and Crypto Investors (N = 163, Panel C). This information is shown in Table 2. Looking at the last column of the Table (B–C), which reveals the average differences between non-crypto and crypto investors along with several characteristics, we can infer that the typical crypto investor is younger (p-value < 0.001), more likely to be male (< 0.001), less optimistic with the real economy (however, such difference is not statistically significant), more risk-tolerant (< 0.001), and more likely to have a background or other course in finance or related area (< 0.01). Furthermore, crypto investors seem to be more confident regarding their investment capabilities (they are more likely to grade themselves as 7–10 on investment performance on a 0–10 scale, p-value < 0.05), more likely to allocate an unexpected additional income in cryptocurrencies (< 0.001), and they do better in the crypto financial literacy test (< 0.001).

In absolute terms, the average crypto investor in our sample lies in the age group 30-39y old (34.4%), is male (only 11.7% of the crypto investors are female, compared to 26.3% in the non-crypto investors' group), and is neutral (35.6%) or pessimistic (36.8%) regarding the prospects of the real economy. Furthermore, the representative crypto investor is moderately aggressive (41.1%) to aggressive (36.8%) and declare to be a self-learning person (55.2%). He is more likely to allocate a fraction of an unexpected marginal income in cryptocurrencies (61.3%) and is likely to correctly identify all three crypto abbreviations in the crypto literacy test (46.6%). The average crypto investor is also less likely to incur type I or type II errors[15] in the crypto literacy test.

Another useful way to understand the differences between crypto and non-crypto investors is to look at Appendix A.1. The reported Figure shows the relative frequencies of occurrence of each profile in Age, Gender, Real Economy Sentiment, Risk Tolerance, Financial Edu-cation, Self-evaluated Investment Performance, Marginal Income in Cryptocurrencies, and Crypto Literacy. Those histograms reinforce the patterns discussed above.

Finally, we report in Table 3 the pairwise correlation coefficients among the variables used in the study. As the Table shows, investing in

[15] A Type I error occurs when the respondent fails to select a true answer. Type II error refers to the respondent selecting at least one false answer.

Table 3
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Crypto Investor	1.00															
(2) Age Group	−0.19*	1.00														
(3) Gender	−0.16*	0.05	1.00													
(4) Real Econ. Sentiment	−0.08	0.03	−0.15*	1.00												
(5) Risk Tolerance	0.25*	−0.23*	−0.23*	0.08	1.00											
(6) Educ. Background	0.12*	−0.13*	−0.17*	0.01	0.18*	1.00										
(7) Perceived invest. performance	0.17*	−0.14*	−0.18*	0.06	0.20*	0.28*	1.00									
(8) Mg Income - No crypto	−0.47*	0.16*	0.11	0.04	−0.30*	−0.06	−0.04	1.00								
(9) Mg Income - Some crypto	0.47*	−0.16*	−0.11	−0.04	0.30*	0.06	0.04	−1.00	1.00							
(10) Mg Income - 100% crypto	0.14*	0.07	−0.02	0.00	0.10	−0.04	0.00	−0.35*	0.35*	1.00						
(11) Crypto Literacy - 3/3	0.52*	−0.23*	−0.17*	−0.04	0.31*	0.10	0.16*	−0.39*	0.39*	0.09	1.00					
(12) Crypto Literacy - 2/3	0.15*	−0.12*	−0.08	−0.03	0.13*	0.11	0.06	−0.10	0.10	0.02	−0.27*	1.00				
(13) Crypto Literacy - 1/3	−0.39*	0.17*	0.08	0.09	−0.24*	−0.07	−0.08	0.27*	−0.27*	−0.04	−0.40*	−0.55*	1.00			
(14) Crypto Literacy - 0/3	−0.20*	0.16*	0.16*	−0.04	−0.16*	−0.16*	−0.14*	0.16*	−0.16*	−0.05	−0.16*	−0.22*	−0.33*	1.00		
(15) Crypto Literacy - Type I error	−0.52*	0.23*	0.17*	0.04	−0.31*	−0.10	−0.16*	0.39*	−0.39*	−0.09	−1.00	0.27*	0.40*	0.16*	1.00	
(16) Crypto Literacy - Type II error	−0.16*	0.14*	0.15*	0.01	−0.09	−0.16*	−0.11*	0.12*	−0.12*	−0.05	−0.14*	−0.17*	−0.31*	0.85*	0.14*	1.00

Note: This table shows the pairwise correlation coefficients among the variables used in this study. * shows statistical significance at the 0.01 level.

crypto is negatively related to age (−0.19) and female (−0.16), and positively related to risk tolerance (0.25), educational background (0.12), perceived investment performance (0.17), and crypto literacy (0.52 with Crypto Literacy 3/3 - correctly identifying all cryptos in the test). Concerning the interrelationship among predictors, we can see that risk tolerance is negatively correlated to age (−.23) and gender (−0.23). Another significant correlation to discuss is the negative association between gender and educational background (−0.17): female investors are also, on average, less likely to have a major in finance or related areas. Importantly, there is no correlation coefficient large enough to raise a flag to multicollinearity concerns in our regressions.[16]

4. Baseline results

4.1. Determinants of cryptocurrency actual and prospective invest-ments

Following the uni-variate, unconditional analyses, we begin our multivariate analysis by analyzing the sociodemographic and behavioral determinants of both past (Past Crypto Investor, Panel A) and potential future cryptocurrency investment (Marginal Income in Crypto, Panel B).[17]

In Table 4 we report the Average Marginal Effects (AMEs) following the logit estimation of Eq. (1). We estimate a range of specifications ranging from the most ([I] and [IV]) to the least parsimonious ([II] and [VI]). All regressions include investment office fixed effects and robust standard errors.

Conditional on investment office fixed effects, we find that females (Female) are 19.8 percentage points (p.p.) and 12.6 p.p. less likely to have invested and to invest a marginal income in cryp-tocurrencies, respectively.[18] In specifications II and V, we add Age (−), Real Economy Optimism (−), Risk Tolerance (+), and Educational Background (no statistically distinguishable from zero effect). Finally, after adding the perceived investment performance in regressions III and VI, we find that self-perceived performance is only significant to explain past crypto investment (Panel A). Furthermore, for the marginal income in crypto (Panel B), the significance of the Female dummy goes away when we add the perceived performance – after controlling for a potential overconfi-dence, the role of gender in choosing cryptocurrency on a portfolio allocation decision disappears. However, for past investments, such an alteration does not occur – female status is significant regardless of perceived investment performance.

Overall, the results from Table 4 indicate that Age (−), Real Economy Optimism (−), and Risk Tolerance (+) are the most robust determinants of cryptocurrency past and future investments. Interestingly, being negatively affected by optimistic views of the real economy suggests that cryptocurrencies may be a valuable asset class to hedge against economic downturns and economic policy uncertainty [57]; for instance, find that the China EPU index can predict negatively the bitcoin monthly volatility.).

4.2. Heterogeneous effects across age groups

Other questions remain, though. For example, are the influence of the predictors homogeneous across age groups? To answer this question, we also show in Table 5 the results from estimating equation (1) in sub-

[16] There are particularly high correlations – for example, Crypto Literacy - 0/3 and Crypto Literacy - Type II error (0.85). However, these variables are different proxies and are never used concomitantly in the same regression specification.

[17] Dummy variable equal to one if he/she selected cryptocurrency as one of the portfolio allocations of an ad-ditional, unexpected marginal income, and zero otherwise. Other alternatives include savings accounts, treasury bonds and bills, private fixed income, foreign fiat currencies, stocks, and commodities. See Question 7 for details.

[18] In all Tables, we report the Average Marginal Effects (AMEs).

Table 4
Likelihood of have invested and invest an unexpected income in cryptocurrencies, full sample, logit models.

Variable	Panel A) Dep. Var. = Past crypto Investment			Panel B) Dep. Var. = Marginal income in crypto		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Female	−0.1978***	−0.1441***	−0.1343***	−0.1259***	−0.0644	−0.0693
	(-3.83)	(-2.78)	(-2.60)	(-2.58)	(-1.35)	(-1.44)
Age		−0.0481***	−0.0440***		−0.0318**	−0.0335**
		(-3.46)	(-3.16)		(-2.22)	(-2.31)
Real Econ. Optimism		−0.0585***	−0.0590***		−0.0388*	−0.0385*
		(-2.61)	(-2.70)		(-1.81)	(-1.78)
Risk Tolerance		0.1038***	0.0971***		0.1420***	0.1444***
		(4.86)	(4.60)		(6.98)	(7.09)
Educ. Background		0.0248	0.0125		−0.0049	−0.0001
		(1.31)	(0.64)		(-0.24)	(-0.00)
Perceived investment performance			0.0294**			−0.0111
			(2.43)			(-0.91)
Obs.	573	573	573	573	573	573
Pseudo R-Sq.	0.023	0.105	0.113	0.010	0.096	0.097
Inv. Office FE	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of the logit estimation of Eq. (1) using alternative dependent variables. *, ** and.
*** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5
Likelihood of investing in cryptocurrencies, conditioning on age groups – logit models.

Variable	Subsamples stratified by age groups									
	Panel A) Dep. Var. = Past crypto Investment					Panel B) Dep. Var. = Mg. income in crypto				
	29≤years	30-39y	40-49y	50-59y	60> years	*29≤years*	30-39y	40-49y	50-59y	60> years
Female	−0.3992**	−0.2664**	−0.1027	0.0182	−0.2902**	−0.2238	−0.0275	−0.3680**	0.0535	−0.0828
	(-2.48)	(-2.39)	(-0.87)	(0.24)	(-2.01)	(-1.26)	(-0.25)	(-2.53)	(0.59)	(-0.94)
Real Econ. Optimism	−0.0677	0.0045	−0.0095	−0.1612***	−0.0326	−0.1938**	−0.0335	−0.0423	−0.0649	0.0256
	(-0.74)	(0.10)	(-0.20)	(-4.04)	(-0.82)	(-2.15)	(-0.73)	(-0.94)	(-1.29)	(0.67)
Risk Tolerance	0.1547***	0.0971*	0.0786	0.1364***	0.0396	0.2220***	0.2038***	0.1490***	0.1688***	0.0547
	(3.68)	(1.90)	(1.53)	(3.64)	(1.07)	(4.82)	(4.43)	(3.71)	(3.96)	(1.55)
Educ. Background	0.0406	0.0052	−0.0164	0.0317	0.0397	0.0600	0.0264	−0.0536	0.0387	0.0205
	(0.52)	(0.13)	(-0.37)	(0.84)	(1.09)	(0.81)	(0.66)	(-1.53)	(0.93)	(0.53)
Perceived investment	0.1047*	0.0308	0.0450*	0.0146	−0.0079	−0.0635	−0.0144	−0.0384*	−0.0396	−0.0059
performance	(1.67)	(1.03)	(1.88)	(0.70)	(-0.35)	(-0.97)	(-0.55)	(-1.77)	(-1.55)	(-0.28)
Obs.	34	156	126	114	143	34	156	126	114	143
Pseudo R-Sq.	.409	.107	.0708	.232	.0938	.39	.0926	.223	.126	.0543
Inv. Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of the logit estimation of Eq. (1) using alternative dependent variables and condi-tioning on different age groups. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

samples stratified by age groups (up to 29 years, 30–39 years, 40–49 years, 50–59 years, and 60+ years). Such empirical exercises suggest interesting patterns. First, while females are less likely to have invested in crypto up to 39 years and from 60 years onward, we got opposite results when considering the investment of a marginal income (the female dummy is negative and statistically significant in the middle of the age distribution – 40-49y). Second, the negative association between optimism with the prospect of the real economy and investing in crypto seems to be concentrated on people at 50–59 years (in other age levels, such association is statistically non-significant) for past investment, and at 29 or less for the marginal investment.

Third, risk tolerance is a key driver of crypto past and marginal investing in crypto for nearly all age groups except for 60+ years. Such a pattern seems to be consistent with [58]; who finds that risk tolerance decreases with age, but only up to a point. After age 65 (retirement), risk tolerance increases with age. In our case, the findings suggest that the demand for crypto assets beyond age 60 is uncorrelated with risk aversion and optimism/pessimism with the real economy. Fourth, the educational background does not seem to be a key driver of crypto investing for any of the age groups. Finally, perceived investment performance appears to be significant in the middle of the age distribution (40-49y), but positive to past and negatively related to marginal investment in crypto.

4.3. Choice of investing a marginal, unexpected income in different financial instruments

Another important issue in understanding the investor's decision-making process is looking at the sociodemographic and behavioral determinants for investing a marginal, unexpected income across different financial instruments. By doing that, we can compare the determinants of crypto investing with those from other risky (say, stocks and commodities) or less risky financial instruments (say, savings accounts and local government bills and bonds). In Fig. 2, we show the number of chosen alternatives for each financial instrument, stratified by past crypto investment status (those that have already invested in crypto and those that have never invested).[19] While among the non-crypto investors cryptocurrency (60) is ranked 5th (stocks [290], private fixed income securities [188], local government bills/bonds [87], and commodities [68] are more common choices), among the crypto investors cryptocurrency (100) only rank behind stocks (123). Thus, past cryptocurrency investment decisions seem to be positively and highly correlated with future ones.

[19] The sum of each alternative does not sum the number of respondents because this is a multiple-answer question.

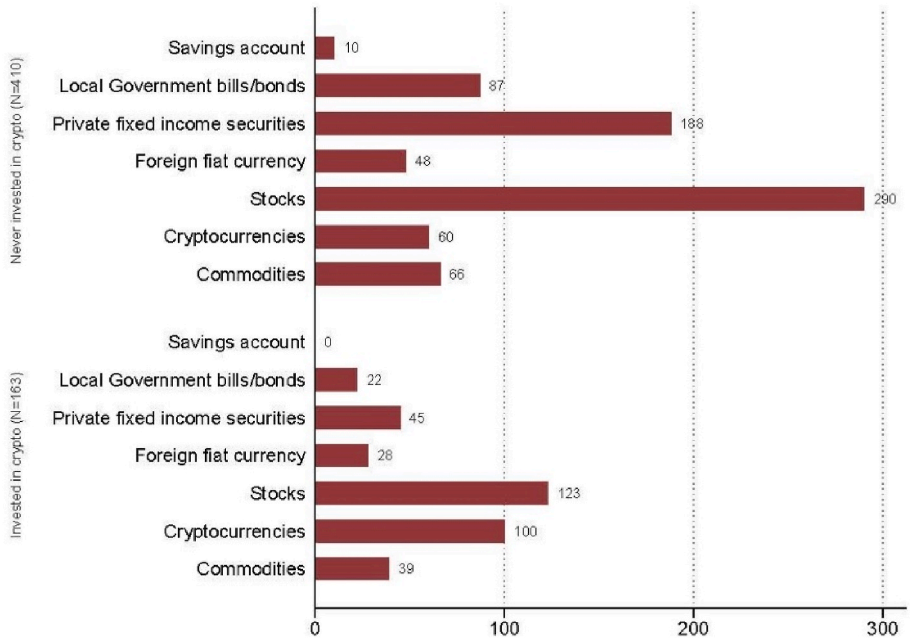

Fig. 2. Which financial instrument to invest an unexpected income? Frequency of responses, by past investment in crypto.

Table 6
Propensity to invest a marginal, unexpected income in different financial instruments.

Variable	Dependent variable						
	Savings Acc.	Treasuries	Priv. Fixed Income	FX	Stocks	Crypto	Commodities
Age	−0.0005	−0.0169	−0.0127	−0.0200*	−0.0513***	−0.0335**	−0.0276**
	(-0.13)	(-1.30)	(-0.80)	(-1.67)	(-3.72)	(-2.31)	(-2.15)
Gender	0.0352**	−0.0102	0.0699	0.0216	0.0046	−0.0693	−0.0311
	(2.22)	(-0.25)	(1.44)	(0.61)	(0.11)	(-1.44)	(-0.69)
Real Econ. Optimism	0.0053	0.0052	−0.0062	−0.0391**	0.0609***	−0.0385*	−0.0034
	(0.79)	(0.26)	(-0.25)	(-2.10)	(2.78)	(-1.78)	(-0.17)
Risk Tolerance	−0.0046	−0.0731***	−0.1201***	−0.0052	0.0982***	0.1444***	0.0163
	(-0.59)	(-3.69)	(-5.25)	(-0.28)	(4.90)	(7.09)	(0.76)
Educ. Background	0.0018	0.0107	−0.0154	0.0290*	0.0402*	−0.0001	0.0441***
	(0.25)	(0.59)	(-0.66)	(1.72)	(1.89)	(-0.00)	(2.60)
Perceived. Inv. Perf.	−0.0006	−0.0249**	−0.0081	0.0004	0.0202*	−0.0111	−0.0158*
	(-0.13)	(-2.53)	(-0.58)	(0.04)	(1.75)	(-0.91)	(-1.72)
Obs.	573	573	573	573	573	573	573
Pseudo R-Sq.	.137	.0451	.0563	.0329	.123	.0971	.0277
Inv. Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of the logit estimation of the likelihood of selecting each investment choice as an allocation for a hypothetical unexpected, marginal income. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

We also estimate the determinants of choosing a given financial instrument as the destination for the hypothetical marginal income (i.e., we consider seven dependent dummy variables from Question 7). We ran the analysis on each financial instrument and not on groups (e.g., risky versus conservative investment instruments) because some risky assets have very different exposure to risk factors, and aggregating them as if they were the same would make us lose the granularity of our data (and, potentially, we would lose interest findings).[20]

Table 6 shows the results. Savings account, the least ranked option in each sub-sample, is systematically related only to gender – females are 3.5 percentage points more likely to select this investment choice than males. Treasury bills/bonds, also a conservative investment alternative, are negatively related to risk tolerance and perceived investment performance. Private fixed income is also more common with conservative investors but is unrelated to the self-assessment of investment achievements.

On the more risky options, FX, cryptocurrencies, and stocks are very similar in the sense that they are a more common choice for younger investors [16]. However, they differ significantly on the role of real economy optimism: while FX and cryptocurrencies are more demanded by investors who are pessimists about the real economy (suggesting a demand for hedging purposes), stocks behave in the opposite direction (i.e., show a pro-cyclical behavior). Thus, FX and cryptocurrency might be interpreted as potential substitute financial instruments to hedge bad expectations on the local economy [9]. Finally, commodities are negatively related to age and perceived investment performance and positively related with a background in finance or related areas. This is consistent with [37]; who showed the importance of investment experience in investment outcomes. Overall, according to our results, we conclude that younger, more educated, and risk-tolerant investors are

[20] For instance, our prior was that FX might substitute for crypto because they may be used to hedge pessimist expectations on the real economy [66]. On the other hand, we expected stocks to be a more suitable choice for individuals who are optimistic about the real economy.

Table 7
Further analysis: the role of crypto financial literacy on the propensity to invest in cryptocurrency.

Variable	Panel A) Dep. Var. = Past Crypto Investment					Panel B) Dep. Var. = Marginal income in crypto				
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Female	−0.1978***	−0.1441***	−0.1343***	−0.0737	−0.0438	−0.1259***	−0.0644	−0.0693	−0.0311	−0.0061
	(-3.83)	(-2.78)	(-2.60)	(-1.61)	(-0.96)	(-2.58)	(-1.35)	(-1.44)	(-0.71)	(-0.14)
Age		−0.0481***	−0.0440***	−0.0193	−0.0024		−0.0318**	−0.0335**	−0.0160	−0.0052
		(-3.46)	(-3.16)	(-1.52)	(-0.20)		(-2.22)	(-2.31)	(-1.12)	(-0.37)
Real Econ. Optimism		−0.0585***	−0.0590***	−0.0434**	−0.0338*		−0.0388*	−0.0385*	−0.0276	−0.0216
		(-2.61)	(-2.70)	(-2.19)	(-1.82)		(-1.81)	(-1.78)	(-1.34)	(-1.08)
Risk Tolerance		0.1038***	0.0971***	0.0391*	0.0077		0.1420***	0.1444***	0.1039***	0.0860***
		(4.86)	(4.60)	(1.95)	(0.38)		(6.98)	(7.09)	(5.10)	(4.17)
Educ. Background		0.0248	0.0125	0.0118	0.0024		−0.0049	−0.0001	−0.0011	−0.0097
		(1.31)	(0.64)	(0.64)	(0.13)		(-0.24)	(-0.00)	(-0.05)	(-0.47)
Perceived investment performance			0.0294**	0.0199*	0.0181*			−0.0111	−0.0166	−0.0191*
			(2.43)	(1.94)	(1.78)			(-0.91)	(-1.51)	(-1.65)
Crypto Literacy 3/3				0.3729***	0.4631***				0.2782***	0.3445***
				(11.00)	(13.73)				(7.35)	(8.24)
Crypto Literacy 2/3					0.2301***					0.1565***
					(6.78)					(3.94)
Crypto Literacy 0/3					−0.0872					−0.0962
					(-1.08)					(-1.30)
Obs.	573	573	573	573	573	573	573	573	573	573
Pseudo R-Sq.	0.023	0.105	0.113	0.244	0.320	0.010	0.096	0.097	0.161	0.192
Inv. Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of the logit estimation of Eq. (1) using alternative dependent variables and including an extra dimension of explanatory variables: results from the crypto literacy test. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

more inclined to invest in risky assets, such as cryptocurrency.

4.4. Further analyses: Cryptocurrency financial literacy and investor sophistication

Including Cryptocurrency Literacy as a regressor. One may question to what extent cryptocurrency financial literacy – rather than overall financial literacy – may explain investment tendency to that asset class. To answer this question, we add proxies for crypto financial literacy as an additional explanatory variable to explain past and marginal crypto investment. In the survey, Question #9, we ask: "Which of the acronyms below do you recognize as cryptocurrency(ies) or token(s)?". There were three cryptocurrency acronyms (BTC, ETH, and XRP) mixed with tickers for other financial instruments unrelated to crypto (WTI – Crude Oil, XAU – Gold Exchange Rate, CHF – Swiss Franc) and a confounder (HDK). We then sort individuals to the extent they could correctly identify 3 out of 3 (Crypto Literacy 3/3), 2 out of 3 (Crypto Literacy 2/3), 1 out of 3 (Crypto Literacy 1/3), and 0 out of 3 (Crypto Literacy 0/3), and use these dummy variables to test for the role of financial literacy on this particular market. The results are shown in Table 7.

The results shown in Table 7 suggest that past and future cryptocurrency investment decisions are intrinsically related to crypto literacy. In particular, based on the full models (specifications [V] and [X]), having correctly answered our cryptocurrency quiz (Crypto Literacy 3/3) increases the likelihood of having already invested and investing a hypothetical marginal income in cryp-tocurrencies in 46.3 and 34.4 p.p., respectively, relative to an investor that correctly identified only bitcoin. Thus, crypto literacy seems to be a vital determinant of crypto investing. Furthermore, including cryptocurrency literacy changes the partial role of other explanatory variables. For instance, age and gender lose statistical significance when crypto literacy is added. On the other hand, self-assessment on investment capabilities, real economy optimism (for past investment only), and risk tolerance (for a marginal investment only) remain significant determinants even if crypto literacy is considered.

Sophisticated vs Unsophisticated investors. Following [32]; we use self-perceived performance to proxy for sophisticated (those that report a high level of performance on investments) and unsophisticated (the ones with low-level self-reported performance in invest-ments) investors. To avoid an arbitrary cutoff, we consider three proxies for sophisticated investors: those self-graded at seven or above (on a 0–10 scale – Soph. 7, N = 327), eight or above (Soph. 8, N = 145), and nine or above (Soph. 9, N = 21). We use these proxies to sort our sample into sophisticated and unsophisticated investors. Results are shown in Table 8.

From Table 8, we can infer that risk tolerance is a systematic determinant for crypto investing, except for sophisticated investors at the 9/10 threshold. For these investors (N = 21), educational background in finance or related (+, p-value <0.05) and perceived investment performance (+, p-value <0.01) seem to be more relevant. Moreover, female status matters more for the unsophisticated (−) than for sophisticated investors. The same pattern can be found for real economy optimism: it is negative and statistically significant at the 5% level for sophisticated investors (7/10 and 8/10), but not for unsophisticated investors in these cutoffs. Thus, using cryptocurrencies to hedge unfavorable expectations regarding the real economy seems to be a phenomenon more prone to sophisticated, knowledgeable investors.

5. Beyond pure ownership: Which factors attract investors to the cryptocurrency ecosystem?

So far, we have analyzed the determinants of investment decisions of cryptocurrency and non-cryptocurrency digital investors. Beyond that, one topic that remains largely unanswered in the literature is what motivates/demotivates investors from entering the cryptocurrency ecosystem [11,12,59,60]. While [9] identify differences between cryptocurrency and non-cryptocurrency investors in their trading preferences and portfolio activity, it is not clear which factors attract (e.g., the long-run potential of the blockchain technology, low correlation, past performance, etc.) and repeal (e.g., volatility, uncertainty on the fair price, risk of fraud, etc.) investors from the ecosystem.

To answer these questions, we rely on the Question "What(which) is (are) the most motivat-ing reason(s) to invest in cryptocurrencies?", where both cryptocurrency (Question 13) and non cryptocurrency investors (Question 20) responded. Each respondent could select multiple options among the alternatives, grouped into *backward looking measures*, *macroeconomic and portfolio drivers*, *technological drivers*, *gambling preferences*, and *other reason(s)*.

Table 8
Further analysis: sophisticated and unsophisticated investors.

Variable	Subsamples stratified by sophisticated/unsophisticated investors											
	Panel A) Dep. Var. = Past Crypto Investment						Panel B) Dep. Var. = Marginal income in crypto					
	Soph. @7	Soph. @8	Soph. @9	Unsoph. @7	Unsoph. @8	Unsoph. @9	Soph. @7	Soph. @8	Soph. @9	Unsoph. @7	Unsoph. @8	Unsoph. @9
Female	−0.1303*	−0.0584	−0.1591	−0.1333*	−0.1502**	−0.1366***	−0.0946	−0.0252	−0.1481	−0.0504	−0.0853	−0.0746
	(-1.73)	(-0.53)	(-0.48)	(-1.86)	(-2.55)	(-2.60)	(-1.27)	(-0.23)	(-0.40)	(-0.78)	(-1.62)	(-1.53)
Real Econ. Optimism	−0.0823***	−0.1068**	−0.0661	−0.0390	−0.0446*	−0.0617***	−0.0465*	−0.0060	−0.0912	−0.0331	−0.0545**	−0.0437**
	(-2.79)	(-2.41)	(-0.78)	(-1.23)	(-1.80)	(-2.76)	(-1.65)	(-0.14)	(-0.91)	(-0.96)	(-2.19)	(-1.97)
Risk Tolerance	0.1500***	0.1546***	0.1190	0.0549*	0.0966***	0.1064***	0.1788***	0.1805***	0.1645	0.1184***	0.1432***	0.1503***
	(5.59)	(3.43)	(0.70)	(1.65)	(4.12)	(5.01)	(6.85)	(3.98)	(0.95)	(3.61)	(6.26)	(7.26)
Educ. Background	−0.0063	−0.0369	0.2249**	0.0498*	0.0329	0.0080	−0.0002	0.0284	0.0003	0.0068	−0.0098	0.0005
	(-0.24)	(-0.89)	(2.28)	(1.77)	(1.53)	(0.39)	(-0.01)	(0.69)	(0.00)	(0.19)	(-0.41)	(0.03)
Perceived investment performance	0.0420	0.0020	0.4458***	0.0241	0.0245	0.0380***	0.0119	−0.0109	0.0409	−0.0114	−0.0135	−0.0098
	(1.31)	(0.03)	(2.89)	(1.04)	(1.51)	(2.71)	(0.39)	(-0.18)	(0.20)	(-0.49)	(-0.83)	(-0.73)
Obs.	327	145	21	246	428	545	327	145	21	246	428	545
Pseudo R-Sq.	.0983	.109	.372	.0861	.0829	.091	.12	.111	.19	.0559	.0845	.0868
Inv. Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of the logit estimation of Eq. (1) using alternative dependent variables and stratifying the sample in sophisticated and unsophisticated investors. Soph. (Unsoph.) 7, Soph. (Unsoph.) 8, Soph (Unsoph.) 9 indicate the cutoff used to define these two subsamples – grade 7 or more, grade 8 or more, grade 9 or more, respectively (in a 0 to 10 scale of self-performance in investments). *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

We begin by showing in Fig. 3 the sum of responses for each of the motivating reasons to invest in cryptocurrencies.[21] Fig. 3a reports the results for the full sample (N = 573): Historic of Growth (216), Long run potential of the technology (190), There is no reason for me to invest (147), Uncorrelation with traditional assets (130), and Uncorrelation with the Brazilian economy (127) are the most cited factors. When we break the whole sample into cryptocurrency investors (Fig. 3b, N = 163) and non-cryptocurrency investors (Figure Fig. 3c, N = 410), we infer that Historic of growth is disproportionately more cited by non-cryptocurrency than cryptocurrency investors. On the other hand, the Long run potential of the technology is far more relevant for the cryptocurrency investors subsample than for non-cryptocurrency investors. Thus, we conclude that cryptocurrency investors are more likely to believe in the underlying technological features of cryptocurrencies (blockchain or other digital ledger technologies – DLTs). In contrast, non-cryptocurrency investors see no reason to invest or are attracted by the cryptocurrencies' historic of growth.

The next step in this analysis is to empirically test whether being a cryptocurrency investor affects the likelihood of a respondent selecting each motivating reason. We also want to analyze the sociodemographic drivers of each motivating/demotivating factor. To do that, we generate eight dummies equal to one if respondent i has selected factor j as a motivating reason to invest and zero otherwise ($j = 1, \ldots, 8$). For example, *Long run potential of the technology* equals one if the respondent has marked that particular motivating factor and zero otherwise. Table 9 shows the AMEs for each predictor, including the dummy for cryptocurrency investors (Cryptocurrency Investor Dummy), after estimating a logistic model for each motivating factor. We can infer from the Table that, although cryptocurrency investors are more likely to be captivated by other factors as well, they are 24.6 p.p. more likely to be attracted by the long-run potential of the technology than an average non-cryptocurrency investor of our sample (see regression [6]). Such a result is not only statistically significant (p-value < 0.01), but also economically meaningful. Furthermore, it sheds light on previous evidence that performance expectancy on cryptocurrencies is a first-order factor for developing a cryptocurrency [61]. Cryptocurrency investors are also more prone to be attracted by backward-looking measures (both historic of growth and popularity, corroborating the trend-chasing behavior found by Ref. [9] and the importance of social learning in shaping investors' perceptions [32], respectively), macroeconomic factors (low correlation with the real economy and with traditional assets), and other reasons.

5.1. Individual-level heterogeneity on cryptocurrency beliefs

Early vs. Late adopters. So far, we have shown that cryptocurrency investors are more likely to be attracted by backward-looking measures (historic growth, popularity), macroeconomic and portfolio factors (low correlation with both the real economy and traditional assets), and technological factors (long-run potential of the technology). However, these perceptions may differ between groups of cryptocurrency investors, like early and late adopters. For example [9], find that early cryptocurrency adopters are more likely to invest early in innovative, high-risk structured products (like emerging market, solar sector, or biotech sector exchange-traded funds), and to follow price trends and invest in sentiment or trending securities.[22] It is not clear in the literature if the beliefs and reasons to invest in cryptocurrencies differ between early and late investors.

To understand if and how the motivations of early and late

[21] We give an option "There is no reason to invest" for those investors that do not have any reason at all to invest in this asset class.

[22] However, because [9] only uses data up to September 2017, they are not able to compare early with late adopters – those that entered the cryptocurrency ecosystem after the wave of institutional adoption (2020 on-wards).

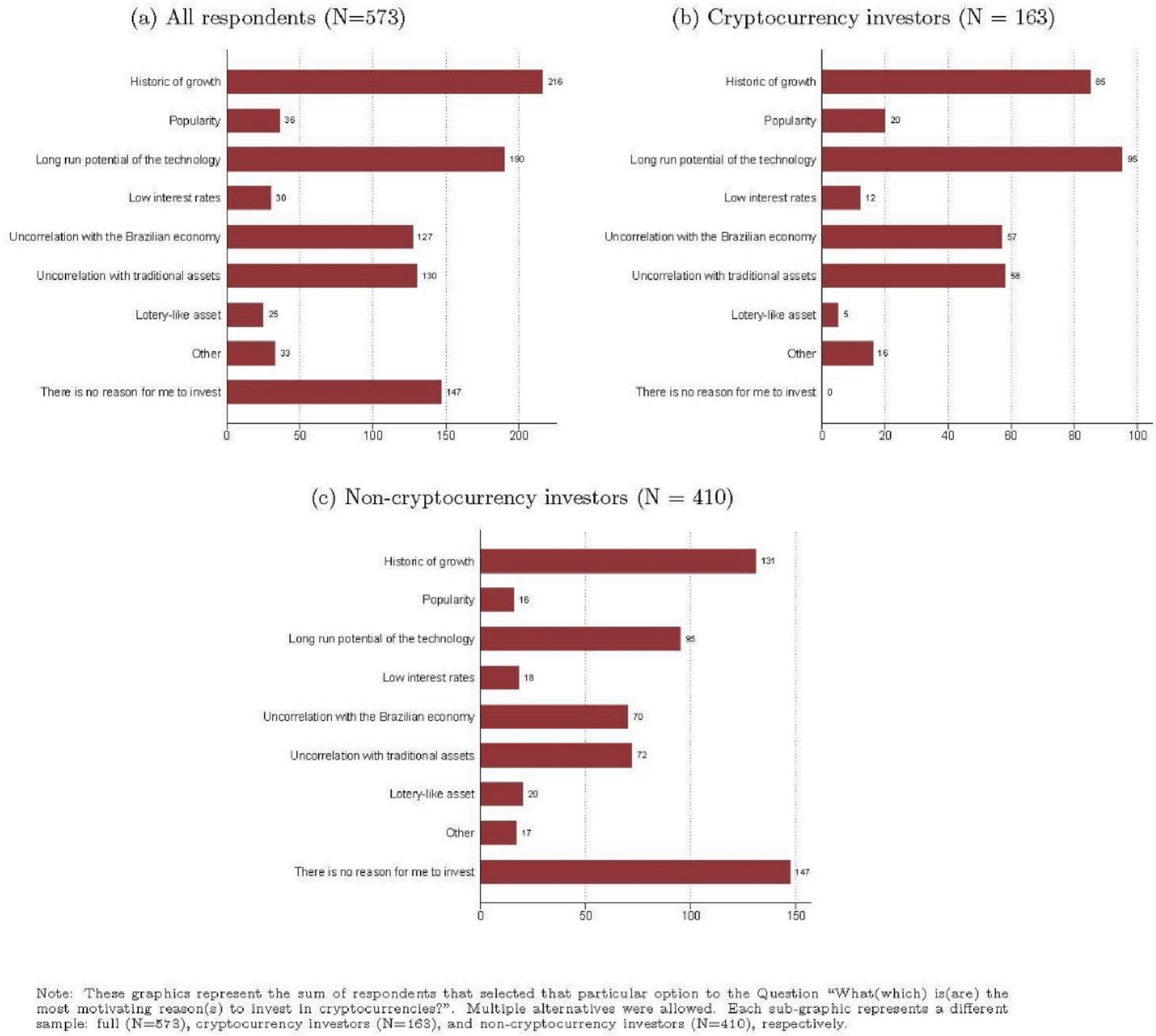

Fig. 3. Motives to invest in cryptocurrencies: full sample, cryptocurrency, and non-cryptocurrency investors
Note: These graphics represent the sum of respondents that selected that particular option to the Question "What(which) is(are) the most motivating reason(s) to invest in cryptocurrencies?". Multiple alternatives were allowed. Each sub-graphic represents a different sample: full (N = 573), cryptocurrency investors (N = 163), and non-cryptocurrency investors (N = 410), respectively.

cryptocurrency investors differ, we separate cryptocurrency investors into two groups: those that invested up to 2019 (early adopters, N = 85) and those that invested in 2020 or later (late adopters, N = 74). As reasons to use these cutoffs, we observe in our sample a spike in the number of new cryptocurrency investors in 2020 (see Fig. 4 – 46.5% or 75 cryptocurrency investors made their first allocation in 2020 or early 2021), a period that coincides with the worldwide extensive institutional adoption that made cryptocurrency mainstream.[23] Thus, we are separating those that invested in cryptocurrencies while it was a niche market from those that invested when it became mainstream.

Panel A of Table 10 shows the average marginal effects (AMEs) on the likelihood to have se-lected each attractive factor (backward-looking, macroeconomic and financial, technological, gam-bling preferences, and other reasons) according to the year of the first cryptocurrency investment. In addition to AMEs, we include the p-value of a *t*-test that the coefficient of the early cryptocur-rency investor dummy and the late cryptocurrency investor dummy are equal.[24] We can see that two factors are statistically different between the groups: low-interest rates (p-value = 0.042) and uncorrelation with the real economy (p-value = 0.047). Specifically, late cryptocurrency investors are more prone to invest because of the environment of low-interest rates, which is reasonable since worldwide interest rates (not only in the Brazilian case) went down in 2020 due to the endogenous monetary policy actions to fight the COVID-19 economic effects. The second critical difference is that late investors are more likely to invest in cryptocurrency because of the low correlation with the real economy – i.e., late investors see cryptocurrencies as a potential hedge to risks associated with economic growth. Again, these results make a lot of sense since economic policy uncertainty was much higher in 2020 and

[23] We also tested the group segmentation considering 2019 as part of the late investment period (2019 on-wards), and the results (unreported) are nearly the same.

[24] Thus, rejecting H0 implies that the coefficients are statistically different.

Table 9
Motivations to invest in cryptocurrency: cryptocurrency x noncryptocurrency investors.

Variables	Backward looking measures		Macroeconomic and portfolio drivers			Technological drivers	Gambling preferences	Other
	Historic of growth	Popularity	Low interest rates	Uncorrelation - real economy	Uncorrelation - traditional assets	Long run potential of the technology	Lotery-like asset	Other reason(s)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crypto Investor Dummy	0.1717***	0.0757***	0.0174	0.1103***	0.1076***	0.2461***	−0.0234	0.0540**
	(0.04)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
Age ≤29y	0.0887	0.0708***	0.0539*	0.0654	0.0057	0.3668***	0.0000	−0.0539
	(0.08)	(0.03)	(0.03)	(0.06)	(0.07)	(0.08)	(.)	(0.05)
Sophisticated investors	−0.1667***	−0.0308	0.0118	0.0013	0.0180	0.0324	0.0464	−0.0085
	(0.06)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)
Female	0.0146	0.0220	0.0231	−0.0150	−0.0621	0.0395	0.0037	0.0240
	(0.05)	(0.02)	(0.02)	(0.04)	(0.05)	(0.05)	(0.02)	(0.02)
Real Econ. Optimism	0.0233	0.0204	−0.0070	−0.0476**	−0.0497**	−0.0151	−0.0016	−0.0129
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Risk Tolerance	0.0764***	0.0069	0.0008	0.0586***	0.0383*	0.0596***	0.0114	−0.0133
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Educ. Background	−0.0209	0.0037	0.0160*	−0.0058	0.0276	0.0062	−0.0023	0.0131
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Perceived investment performance	0.0096	−0.0043	0.0026	0.0043	0.0132	0.0017	−0.0077	0.0063
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Obs.	573	573	573	573	573	573	539	573
Pseudo R-Sq.	0.056	0.102	0.055	0.063	0.066	0.134	0.025	0.059
Inv. Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

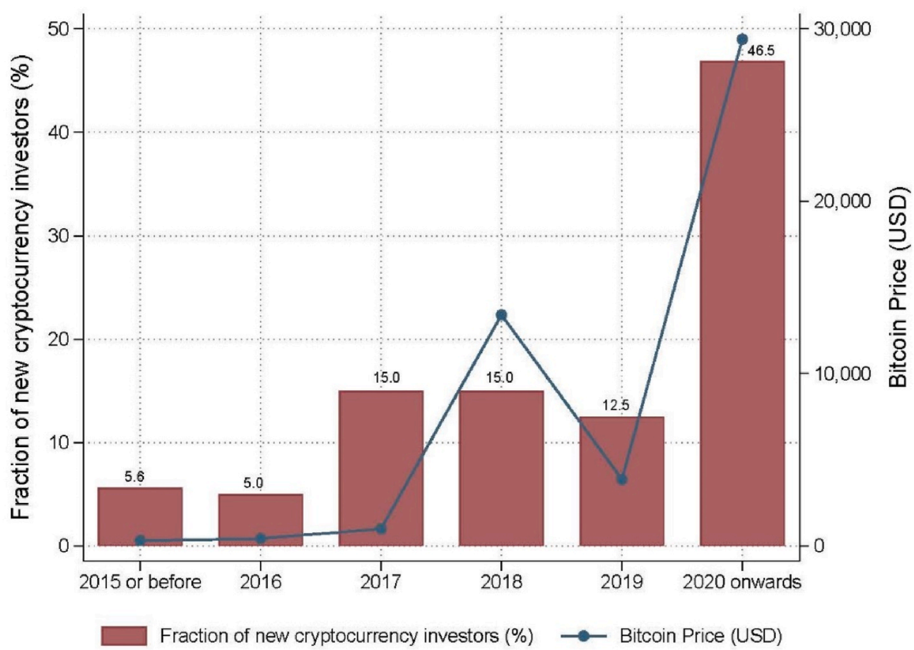

Fig. 4. Year of the first cryptocurrency investment (N = 160 cryptocurrency investors) and evolution of bitcoin price (USD).

early 2021 than in previous years. Thus there were more real economic risks to hedge in that particular period.[25]

Some differences between early and late cryptocurrency investors are not statistically significant (potentially due to the relatively small sample size) but are worth mentioning. First, early investors are more likely to see cryptocurrencies as a lottery-like type of asset, which is consistent with the idea that uncertainty in the value of cryptocurrencies was more considerable during its early days. Buying cryptocurrency as a lottery-type of security is, thus, a potential driver for cryptocurrency demand when it was not yet mainstream, and such behavior is consistent with previous evidence that regular gamblers are more likely to trade cryptocurrencies [62]. In addi-tion [9], also find a positive association between lottery stock preferences and cryptocurrency investments. A second statistically non-significant but potentially economically significant difference is that early investors are relatively more attracted by the low correlation with the returns of traditional assets than late investors. Putting these findings together, we infer that the low correlation

[25] The Global Economic Policy Uncertainty Index (EPU) (see https://www.policyuncertainty.com/) reached a record of 437.17 in April 2020, right after the World Health Organization declared COVID-19 a pandemic. Compared to the previous years (when early investors entered the market), the EPU was about two to three times larger during 2020 and early 2021 (when late investors entered the cryptocurrency ecosystem).

Table 10
Individual-level heterogeneity on the motivating reasons to invest in cryptocurrency.

Variables	Backward looking measures		Macroeconomic and portfolio drivers			Technological drivers	Gambling preferences	Other
	Historic of growth	Popularity	Low interest rates	Uncorrelation w/ real economy	Uncorrelation w/ traditional assets	Long run potential of the technology	Lottery-like asset	Other reason(s)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Early x Late cryptocurrency investors								
Early crypto investor (1)	0.1497***	0.0891***	−0.0266	0.0643	0.1513***	0.2289***	0.0007	0.0674***
	(0.05)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)
Late crypto investor (2)	0.2308***	0.0644**	0.0454**	0.1697***	0.0715	0.2888***	−0.0645	0.0423
	(0.06)	(0.03)	(0.02)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)
Diff. (1)–(2) p-value	[.251]	[.384]	[.042]	[.0471]	[.142]	[.333]	[.202]	[.393]
Obs.	573	573	573	573	573	573	539	573
Pseudo R-Sq.	.0617	.108	.0772	.0709	.0715	.14	.0347	.0641
Panel B: Young x Mature cryptocurrency investors								
Young crypto Investor (3)	0.2237***	0.1156***	0.0281	0.1724***	0.0984**	0.3707***	−0.0311	0.0511*
	(0.06)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)
Mature crypto investor (4)	0.1396***	0.0324	0.0180	0.0615	0.1154***	0.1790***	−0.0225	0.0531**
	(0.05)	(0.03)	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)	(0.02)
Diff. (3)–(4) p-value	[.23]	[.00725]	[.729]	[.0381]	[.754]	[.00197]	[.819]	[.947]
Obs.	573	573	573	573	573	573	573	573
Pseudo R-Sq.	.0566	.114	.041	.0679	.0664	.116	.0269	.0538
Panel C: Sophisticated x Unsophisticated cryptocurrency investors								
Sophisticated crypto Investor (5)	0.0408	0.0323	0.0495*	0.1033*	0.1603***	0.3207***	−0.0147	−0.0016
	(0.07)	(0.04)	(0.03)	(0.05)	(0.05)	(0.06)	(0.04)	(0.04)
Unsophisticated crypto investor (6)	0.2175***	0.0848***	−0.0075	0.1134***	0.0816*	0.2143***	−0.0268	0.0728***
	(0.05)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)
Diff. (5)–(6) p-value	[.0254]	[.178]	[.0991]	[.871]	[.204]	[.133]	[.777]	[.0523]
Obs.	573	573	573	573	573	573	539	573
Pseudo R-Sq.	.0526	.107	.0664	.0626	.0686	.136	.0103	.0753
Panel D: Male x Female cryptocurrency investors								
Male Crypto Investor (7)	0.1725***	0.0725***	0.0161	0.1245***	0.1157***	0.2608***	−0.0279	0.0471**
	(0.04)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)
Female Crypto Investor (8)	0.1104	0.0715*	0.0045	0.0073	0.0984	0.1047	0.0027	0.0720*
	(0.10)	(0.04)	(0.05)	(0.09)	(0.08)	(0.09)	(0.05)	(0.04)
Diff. (7)–(8) p-value	[.558]	[.98]	[.838]	[.218]	[.842]	[.0882]	[.539]	[.493]
Obs.	573	573	573	573	573	573	539	573
Pseudo R-Sq.	.0465	.0961	.0498	.0651	.0632	.136	.011	.0561
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Behavioral controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inv. Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results of the logit estimation of our baseline specification considering different stratification of cryptocurrency investors as predictors. The dependent variable is a binary indicator equal to one if the investor has selected that particular motivating reason to invest in cryptocurrency and zero otherwise (columns 1–8). Panel A: Early (late) crypto investor dummy is equal to one if the first investment occurred up to (after) 2019. Panel B: Young (mature) crypto investor dummy equals one for cryptocurrency investors aged up to 39 years old (40 years old or more). Panel C: Sophisticated (unsophisticated) crypto investor dummy equals one if the respondent has already invested in cryptocurrencies and has evaluated her investment performance as eight or more (up to seven) in a 0–10 scale. Panel D: Male (female) crypto investor equals one for male (female) cryptocurrency investors. Each panel represents a different set of logit regressions that control for the respondent's sociodemographic and behavioral aspects and investment office fixed effects (unreported). Each panel includes the p-value of a *t*-test of difference of means for the indicated coefficients (e.g., early x late crypto investors, Panel A). We report each logit regression's Average Marginal Effects and robust standard errors (in parentheses). *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

motivation for cryptocurrency investment shifted from co-movements with traditional assets in the early days to co-movements with the real economy nowadays (which is a plausible behavior since economic uncertainty has skyrocketed since COVID-19).

Young vs. Mature cryptocurrency investors. A second potential dimension of heterogeneity in the motivating reasons to invest is the age of the cryptocurrency investor. Past research has shown that older investors' portfolio decisions reflect greater knowledge about investing, but investing skills deteriorate with age due to the adverse effects of cognitive aging [63]. Furthermore, younger investors are generally more prone to invest in lottery-type stocks [64]. However, those results are focused on the stock market, and very little is known about how young and experienced cryptocurrency investors differ.[26]

Panel B of Table 10 shows that, conditional on other sociodemographic and behavioral factors, young investors' decisions to invest in cryptocurrency are more likely to be driven by the popularity (p-value = 0.007), uncorrelation with the real economy (p-value = 0.0381), and long-run potential of the technology (p-value = 0.00197) than their mature counterparts. These results suggest that young cryptocurrency investors are indeed different: the extent to which the asset is perceived as popular and the belief on blockchain technology are more critical factors for them. Contrary to past research, we find no differences between mature and young investors in searching for lottery-like assets.

Sophisticated vs unsophisticated investors. Another potential source of heterogeneity in beliefs is sophistication [32]. find that sophisticated investors are less prone to social learning effects in investment decisions than their unsophisticated peers. In the cryptocurrency context, empirical evidence on how financial sophistication shapes beliefs is understudied.

As Panel C of Table 10 shows, sophisticated investors are more (less)

[26] For example, also in a survey context [29], find that late investors and younger individuals with lower income are more optimistic about the future value of cryptocurrencies.

likely to perceive low-interest rates (other reason(s)) as a motivating factor, ceteris paribus. Such a result suggests that macroeconomic factors, in particular the interest rate environment, are considered by sophisticated investors when deciding to invest or not in cryptocurrency. Moreover, other reason(s) – everything unexplained by the previous seven features – are more likely to explain the investment decisions of unsophisticated investors. Those other reasons potentially capture features beyond macroeconomic and portfolio drivers, technological drivers, gambling preferences, and popularity.

Male vs Female investors. Finally, we analyze whether male and female investors differ in the motivating reasons to invest in cryptocurrency. Besides traditional research showing that males are generally more overconfident and trade more than females [37], recent research in the fintech space shows that women worry more about their security when dealing with companies online and are less willing to adopt new financial technology, such as digital banks, than men [33].

To analyze potential differences in attitudes toward cryptocurrencies, Panel D of Table 10 shows the differences between male and female cryptocurrency investors. The only driver of adoption that shows statistically significant differences (p-value = 0.0882) is the long-run potential of the technology: males are more confident in the underlying technology (DLTs - distributed ledger technologies) than females. Such a result corroborates with [33] as it suggests that women and men differ in their attitudes towards new technologies, particularly cryptocurrencies. Overall, the analysis of the heterogeneous beliefs and attitudes indicates that not all cryp-tocurrency investors are equal. On the contrary: their perceptions vary significantly. Mapping and discussing such differences offers an important contribution to past papers on attitudes to-wards crypto investment [11,12]. Furthermore, this analysis is vital for policy-makers and regulators in designing policies for further adoption, particularly in light of the current trend where nearly all central banks are actively engaged in CBDC projects.

6. Concluding remarks

Based on 573 responses (410 non-crypto and 163 crypto investors) to a proprietary questionnaire applied to Brazilian investors throughout five investment offices partners of this research project, we find that cryptocurrency investors are, on average, younger, more tolerant to risk, less optimistic regarding the real economy, more likely to be male and evaluate themselves as better investors than the non-cryptocurrency investors. Contrasting these sharp differences in investor behavior and characteristics, we find that crypto and non-crypto investors are similar in terms of educational background in finance or related areas. Moreover, while cryptocurrency literacy (based on a test of knowledge of cryptocurrency acronyms) is positive and strongly related to past and prospective investments in cryptocurrency, we find that sophisticated investors are more likely to demand cryptocurrency to hedge against the real economy's risks.

Interestingly, predictors of crypto investment seem to vary across age groups. For younger investors (up to 39 years old, N = 190), gender (females less likely to) and risk tolerance (+) are robust determinants of cryptocurrency investment. In the middle of the age distribution (40–59y, N = 240), risk tolerance (+) and optimism with the real economy (−) dominate. Finally, in the elderly group (60+, N = 143), the only systematic predictor of crypto investment is gender (females are less likely to invest). The investment of a hypothetical unexpected income in cryptocurrencies is far more related to risk tolerance and less related to the other explanatory variables across all age groups.

We also analyze individual-level heterogeneity in the beliefs and attitudes toward cryptocur-rencies. Our core findings reveal that late investors are more likely to be attracted by past returns and low-interest rates than early adopters. Meanwhile, the key distinction between young and ex-perienced investors' beliefs is that the former is attracted by popularity and uncorrelation with the real economy. Critical differences between unsophisticated (more likely to invest because of past returns) and sophisticated, males (more confident in the long-run potential of DLT technology) and females are also found.

Overall, our results have practical implications for investors, regulators, and digital asset man-agers. By identifying key differences and similarities between crypto and non-crypto investors, as well as understanding heterogeneity among cryptocurrency investors in attitudes toward cryp-tocurrency in a country of large adoption but still under-investigated, we expand a growing but still incipient literature on the characteristics and behavior of crypto investors [9,20,28,29,35]. Taken together, our results help policymakers to design wider adoption of digital assets in the brave new world of CBDCs and tokenized economies. The results are particularly relevant, considering the increased uncertainty regarding the planned introduction of CBDCs in Brazil, and they might be used for future research in this important area [4].

To the best of our knowledge, this is the first study to use an identification strategy that takes advantage of a large number of clients of digital investment offices that offer both crypto and non-crypto products and services. By doing that, we clearly delimit who are the respondents (all investors) and are able to exploit a significant number of respondents that hold and do not hold cryptocurrency. As limitations, our data comes from a single country (Brazil) and may be biased regarding the characteristics of the respondents, since the portfolio of clients of our partnering investment offices may differ from the national profile. It is also important to note that our responses were collected during Feb.–Mar. 2021, a period of a bull market in the crypto eco-space, which may have biased the responses towards cryptocurrency, especially when we ask how the respondent would invest a hypothetical marginal income. Finally, we want to acknowledge the limitations of our survey design itself, such as using a single question and an acronym detection test to capture financial literacy. This approach might be extended in future studies to better distinguish between sophisticated and non-sophisticated investors.

Future studies can address specific factors underlying the decision to invest in or abstain from crypto-assets, employing matching procedures to achieve balance in observable dimensions between groups. An existing gap lies in understanding whether crypto investors possess a higher degree of cryptocurrency financial literacy. Additionally, applying a similar questionnaire in other countries and during a bear market in the crypto space would be intriguing.

CRediT authorship contribution statement

Jéfferson Augusto Colombo: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft. **Larisa Yarovaya:** Conceptualization, Formal analysis, Investigation, Project administration, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2024.102468.

A Appendix.

A.1 Histogram of the core explanatory variables, by Crypto and Non-Crypto investors

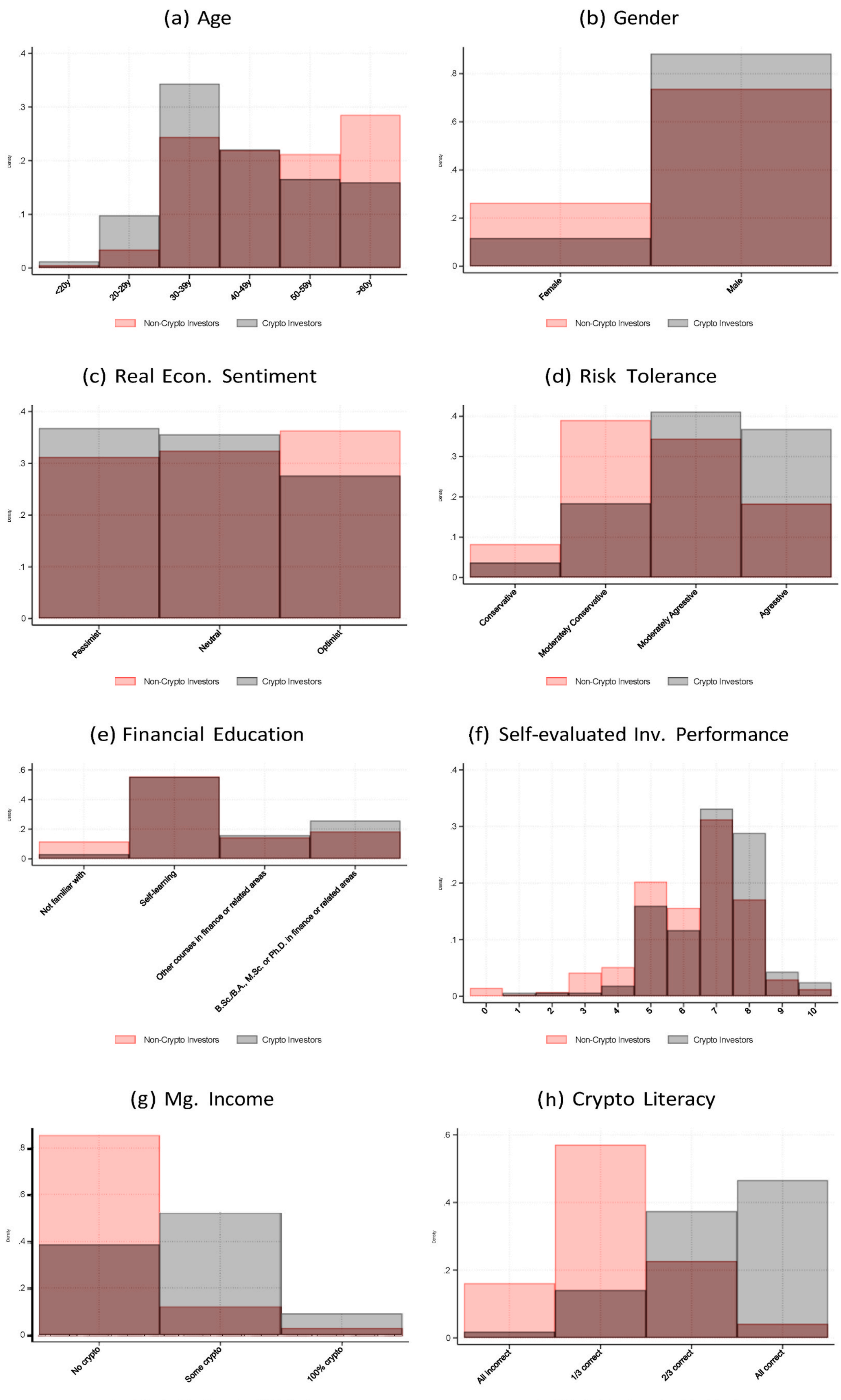

Fig. 5. Histogram of the core explanatory variables

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