Banc Ceannais na hÉireann
Central Bank of Ireland
Eurosystem

Research Technical Paper

Mitigating Vulnerability: The Role of Risk Warnings, Information Order & Salience in Crypto Assets

Danish Us-Salam

Vol. 2025, No. 9

Mitigating Vulnerability: The Role of Risk Warnings, Information Order & Salience in Crypto Assets

Danish Us-Salam[†]

Abstract

The growing popularity of crypto assets has driven increased engagement, often fuelled by promotional content that highlights past returns while downplaying risks. This paper evaluates the effectiveness of behaviourally informed risk warnings in such a setting. Using an online randomized controlled trial, participants viewed simulated investment promotions for two financial products: stocks and crypto assets. Treatments combined behaviorally informed risk warnings with past return information, the same information but with returns shown before warnings, or risk warnings paired with price volatility cues. The first treatment significantly improved risk comprehension and perception by 5% and 4%. These effects are further magnified by the order in which information is presented and by increasing the salience of risk information. Showing risk warnings after potential returns increases risk comprehension by 12% and risk perception by 6%, suggesting evidence in favor of recency bias. Similarly, showing risk warnings and price volatility cues improves risk comprehension by 10% and risk perception by 7%, reflecting the effect of heightened risk salience. These effects are driven by at-risk investors, defined as individuals who follow crypto market updates on social media but have not yet invested in crypto assets. In line with prior evidence, we find no effect among those who have previously invested in crypto assets, likely because their decisions are shaped more by past investment outcomes than by ex-ante warnings.

JEL classification: D83, G11, G41, C93, G53

Keywords: Crypto Assets, Risk Warnings, Order of Information, Recency Bias, Salience

---

[†]Behavioural Consumer Finance Unit, Central Bank of Ireland; danish.ussalam@centralbank.ie. We appreciate participants at the CBI Econ Seminar (Dublin), SABE Conference 2025, and internal policy personnel within the bank for helpful suggestions and comments. We are grateful to Jane Kelly, Yvonne McCarthy, Anu Jose, Alexis Ladasic, and James Carroll for thought-provoking discussions and suggestions. The views in this paper are those of the author only and not of the Central Bank of Ireland.

1 Non-Technical Summary

Crypto assets have grown in popularity, often promoted through content that highlights past returns while downplaying risks. This paper examines how behaviorally informed risk warnings, combined with return information or price volatility cues, can influence how retail investors comprehend and perceive the risks of crypto asset investments. Risk comprehension is defined as consumers' awareness of the maximum possible loss and the level of protection they can expect if things go wrong after investing in crypto assets. Risk perception, on the other hand, refers to investors' ability to judge how risky crypto asset investments are. Using a nationally representative sample, we conducted an online experiment where participants viewed stock and crypto asset promotions. Stocks always included standard warnings. Crypto promotions varied across four groups: a control group with standard warnings and three treatments combining behaviorally informed warnings with (i) return information, (ii) reordered information, or (iii) price volatility cues. Our study reveals four key findings:

1. When behaviorally informed risk warnings were paired with return information, risk comprehension improved by 5% and risk perception by 4% relative to the control group.

2. Presenting risk warnings after showcasing potential returns amplifies their effectiveness. This approach improved risk comprehension by 12% and risk perception by 6%, suggesting that the order of information plays a critical role, leveraging cognitive biases like the recency effect.

3. Highlighting the volatility of crypto markets alongside risk warnings further improves risk comprehension by 10% and risk perception by 7%. Combining warnings with detailed risk information, such as volatility, increases the salience of risk, further enhancing investors' ability to grasp the risks involved.

4. The improvements are concentrated among participants who follow crypto updates on social media but haven't yet invested. We refer to these as at-risk investors because they are most vulnerable to persuasive crypto asset promotions. No effects were observed among individuals who had already invested in crypto assets, likely because their decisions rely more on investment outcomes than risk warnings.

These findings suggest that well-designed risk warnings, combined with an understanding of how people process information, can protect individuals from making poorly informed decisions. The study advocates for regulators to adopt behaviorally informed approaches to investor education and risk communication, helping to balance the appeal of high-risk investments with their inherent dangers.

2 Introduction

The crypto asset market began in 2008 with the release of Satoshi Nakamoto's Bitcoin white paper (Nakamoto, 2008); the first decentralized digital currency built on blockchain technology. This marked the beginning of a financial revolution, introducing the idea of a global currency not controlled by any central authority. Initially met with skepticism, the market has since evolved into a global financial ecosystem with thousands of crypto assets, including Ethereum, Ripple, and Solana. Market capitalization has grown from under $1 billion in 2013 to over $3 trillion at its peak in January 2025 (CMC, 2025). Trading volumes now regularly exceed hundreds of billions of dollars per day, with $115 billion in January 2025 (CMC, 2025), reflecting both rapid market expansion and growing integration with mainstream finance.

This growth has been driven by institutional adoption, technological innovation, and increasing retail investor interest worldwide. In Europe, the crypto landscape is becoming a pivotal part of the continent's financial future, opening new frontiers for financial markets. As of 2023, Europe accounts for a significant share of global crypto asset activity. According to Statista's Global Consumer Survey (Statista, 2023), Switzerland leads (Figure 1) in adoption with 21% of the population reporting ownership or usage, followed closely by the Netherlands (19%) and Norway (17%). Ireland also shows strong engagement, rising from 13% in 2021 to 16% in 2023. Similar upward trends are observed across Belgium, Spain, and Austria, indicating widespread consumer interest.

Recent years have witnessed a significant shift in investment behavior, characterized by increased interest in crypto assets. The economic uncertainty and market volatility induced by the pandemic have prompted investors to seek higher returns, often at the expense of greater risk (Lee, 2022; Zheng et al., 2021). This trend is particularly pronounced among new investors, many of whom lack the financial literacy to fully comprehend the risks associated with investments in crypto assets (Berliana et al., 2022; BIS, 2021). Inexperienced investors are particularly at risk as information on social media platforms and aggressive marketing campaigns can positively influence their investment decisions (Balu et al., 2023; Fiqri and Oetarjo, 2023). Experimental evidence suggests that individual investors increasingly rely on low-quality investment advice from social media platforms. Even advice with little, if any, predictive value appears to influence investor decisions (Kadous et al., 2024).

High-risk investment markets like crypto assets are typically dominated by irrational investors (Almeida and Gonçalves, 2023). While a variety of socioeconomic factors influence consumers' decisions to buy crypto assets (Balutel et al., 2022; Bannier et al., 2019; Fujiki, 2020; Hasso et al., 2019; Panos et al., 2020), a growing body of literature finds that crypto investors are mostly affected by social influence or public sentiment (Almeida and Gonçalves, 2023). Moreover, influencer tweets (Yamamoto et al., 2019; Aditya et al., 2022), forum posts (Mai et al., 2016), Google search trends (Mittal et al., 2019), and crypto asset sentiments on X/Twitter (Steinert and Herff, 2018; Ludwig and Perkowski, 2021) have all been found to influence investor decisions by predicting returns and fluctuations in crypto asset values. Therefore, inexperienced investors, especially those with low levels of investment experience and financial literacy, relying on social media for crypto asset advice, are at a higher risk of making poorly informed investment decisions (Mirtaheri et al., 2021; Kawai et al., 2023).

	2021	2022	2023
Switzerland	13%	18%	21%
Netherlands	10%	19%	19%
Norway	9%	15%	17%
Belgium	10%	15%	16%
Ireland	13%	15%	16%
Spain	10%	15%	15%
Austria	8%	14%	14%
Poland	8%	11%	14%
Denmark	11%	12%	13%
Finland	6%	11%	12%
Germany	6%	12%	12%
United Kingdom	5%	10%	12%
France	5%	9%	11%
Italy	5%	10%	11%
Sweden	6%	11%	11%

Source: Statista Consumer Insights

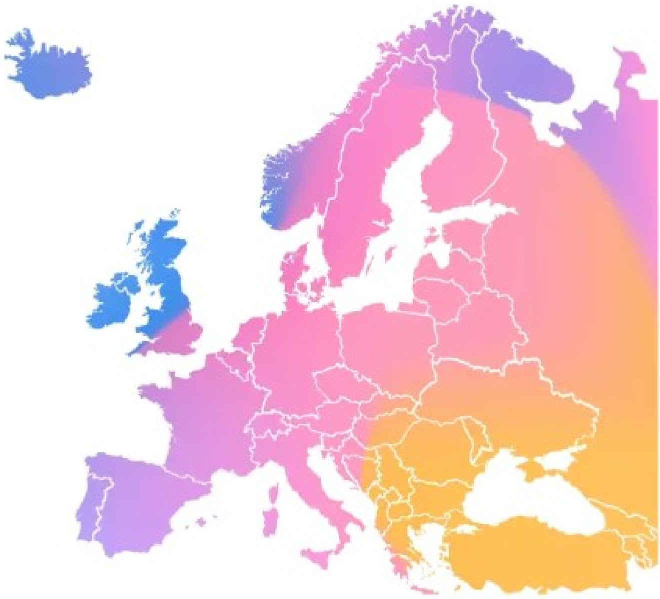


Figure 1. Crypto Asset Ownership & Usage in Europe

When high-profile figures with extensive followings promote high-risk financial products, the potential for widespread, poorly informed investor action escalates dramatically. Empirical evidence suggests that endorsements by celebrities and social media influencers can substantially increase retail investor engagement. However, such exposure also amplifies risks and losses, particularly for less financially sophisticated individuals who are more susceptible to persuasive marketing and speculative narratives (Senz, 2023; Jagolinzer, 2024). These issues are increasingly relevant in light of developments this year in the United States, where the new administration has actively promoted widespread usage of crypto assets (Krause, 2025). In this context, the inclusion of clear and salient risk disclosures becomes critical, not only to temper the effects of promotional hype but also to mitigate the likelihood of suboptimal investment decisions among vulnerable investor segments.

Given high levels of uncertainty and the risky nature of crypto asset markets (Almeida et al., 2022), it is important to identify effective interventions that can improve risk comprehension and perception among investors, especially for people with low levels of investment experience and financial literacy.[1] Financial education programs (Gui et al., 2020; Shavit et al., 2016), encouraging individuals to seek investment advice (Tseng, 2013), and regulatory measures (Baker and Filbeck, 2015) have all been shown to significantly reduce individuals' tendency to invest in high-risk products through improvements in perceived risk.[2] Another tool that has received considerable attention and has often shown mixed evidence is behaviorally informed risk warnings or information disclosures, usually based on behavioral concepts that can be delivered online or in a field setting.[3] On the one hand, experimental evidence by (Delias et al., 2022) shows that risk warnings that are more salient and informative for consumers, and informed by behavioral science, significantly increase consumers' comprehension and perception of the risks involved in high-risk investments. On the other hand, a large-scale experiment by (Seira et al., 2017) in the credit card market for a large population of indebted cardholders found that providing salient interest rate disclosures had no effects on default, indebtedness, account closings, and credit scores.

This paper builds on the nascent crypto asset literature and seeks to provide a rigorous answer to three questions. First, do behaviorally informed risk warnings combined with returns information or price volatility cues improve risk comprehension and risk perception for crypto assets?[4] Second, does changing the order of information further improve risk comprehension and risk perception for crypto assets? Third, do behaviorally informed risk warnings work for at-risk investors? The answers to these questions are important since they have significant implications for regulatory policies and investor protection strategies. Understanding these dynamics can help in designing more effective educational tools and interventions, thereby reducing the susceptibility of less experienced investors to high-risk financial products and ultimately promoting consumer protection, financial stability, and inclusion.

To answer these questions, we designed an online experiment in which participants engaged in a simulated investment browsing experience involving two mock-ups of financial promotions. The first product, always stocks, included a standard risk warning:

1 (Huber et al., 2019) provides experimental evidence suggesting that investor risk perception significantly influences asset prices and trading behavior.

2 (Carbó-Valverde et al., 2025) uses machine learning methods to find a negative association between financial literacy and crypto asset ownership.

3 See (Durkin and Elliehausen, 2011; Williams, 2005; Kroszner, 2007; Lacko and Pappalardo, 2007) and (Woodward and Hall, 2012) for details.

4 We define risk comprehension as consumers' awareness of the maximum possible loss and the level of protection they can expect if things go wrong after investing in crypto assets. This is measured using four quiz-style questions that participants would answer correctly only if they had read and understood the information provided in the treatment. Risk perception, on the other hand, refers to investors' ability to judge how risky an investment is. Participants rate the investment on a scale from 1 to 10, where 1 means not risky at all and 10 means highly risky.

'Your capital is at risk.' The second product, a high-risk investment (crypto assets), featured behaviorally informed risk warnings and varied information about crypto market returns, price volatility, or neutral information, depending on the treatment arm. Following the browsing experience, participants were asked questions to assess their risk comprehension, beliefs, and the extent to which they would recommend investments in stocks or crypto assets to a hypothetical friend.

We find that behaviorally informed risk warnings, coupled with information about crypto asset returns, significantly improved risk comprehension of crypto assets from 68% in the control group to 71% in the treatment group (a 3.1 percentage points or 4.5% increase). Similarly, risk perception for crypto assets improves by 0.327 points on a 10-point scale (a 4% increase relative to the control group mean of 8.243). Adjusting the order of the information further boosts these treatment effects by 7.8 percentage points (a 12% increase relative to the control group) for risk comprehension and 0.458 points for risk perception (a 6% increase relative to the control group). The treatment arm with warnings and volatility information also led to significant improvements in risk comprehension and risk perception for crypto assets by 9.5% and 7.5%, respectively. Additionally, we observe a significant 8% to 15% increase in recommendations for stocks across treatment arms and a statistically insignificant reduction of 2.5% in the risk perception of stocks. We believe this to be an unintended consequence of our treatment, where improved risk comprehension and perception of crypto assets lead respondents to view stocks as less risky and consequently recommend investments; a finding consistent with (Delias et al., 2022). Heterogeneity analysis further suggests that our treatment effects are primarily driven by at-risk investors, which we define as individuals who follow social media for crypto asset updates but have not yet invested in crypto assets.

Our study builds on the work by (Delias et al., 2022) and makes three important contributions. First, we provide causal evidence on the effectiveness of behaviorally informed risk warnings in a setting that closely mimics real-world conditions. Specifically, in addition to risk warnings, we provide information about historical returns. This approach allows us to evaluate the impact of risk warnings within a more complex environment, reflecting the reality that investors typically have access to historical return data, which is often leveraged by crypto asset providers to attract novice investors. Given that historical performance data plays a critical role in attracting investors by showcasing potential gains based on past data (Auti, 2023; Zhu et al., 2021), our design of the investment browsing experience comes closer to how novice investors may see information in the real world.

Secondly, we test whether the order of information can enhance risk comprehension and perception associated with investments in crypto assets. By presenting respondents with crypto asset returns followed by risk warnings, we hypothesize that the salience of the last-viewed information, namely the risk warnings, will be heightened. The recall of the risk warnings in respondents' memory would lead to further improvements and understanding of the risks involved with investments in crypto assets. This is based on the concept of belief-adjustment theory proposed by (Hogarth and Einhorn, 1992) which predicts that when two sets of available information have different content (mixed information), such as good and bad news (in our case risk warnings and potential returns), and are presented in a sequence, people tend to revise their initial belief in a decision. This is linked to recency bias, which refers to the tendency of individuals to place more weight on recent information than previous information.[5]

Finally, by constructing an at-risk investors group in our data, we provide the first causal evidence of our treatment on respondents who are potentially vulnerable to aggressive marketing campaigns. We define this at-risk investor group as participants who follow crypto assets on social media but haven't invested in crypto assets yet. This relates to the work by (Merkley et al., 2024) who studied tweets issued by 180 of the most prominent crypto social media influencers covering over 1,600 crypto assets for two years and found these tweets to be associated with significant negative longer-horizon returns. Since people with low levels of financial acumen are more likely to rely on social media advice for investment decisions (Kadous et al., 2024), understanding the effects of behaviorally informed risk warnings on this group is crucial.

The rest of the paper proceeds as follows. In Sections 2 and 3, we provide the behavioral context and relevant literature for our research. Sections 4 and 5 provide stylised facts and outline our recruitment strategy and intervention details. Sections 6 and 7 describe the sample and empirical strategy. Section 8 reports and discusses our experimental treatment effects. Finally, Section 9 concludes.

3 Context in Literature

3.1 Provision of Information

A growing body of literature studies the impact of information provision on decision-making in various contexts. For instance, (Jensen, 2010) studies the returns to a college degree; (Hastings and Weinstein, 2008) focuses on school test scores; (Jin and Leslie, 2003) explores restaurant hygiene grades; (Bollinger et al., 2011) looks at food calorie information; (Bertrand and Morse, 2011) investigates payday lending; and (Seira et al.,

[5] The results of several previous studies empirically supporting the recency bias in decision-making include (Loewenstein et al., 2003; Hartono, 2004; Alvia and Sulistiawan, 2010) and (Baker and Puttonen, 2017).

2017) studies indebted cardholders in the credit card market. However, research evaluating the impact of information provision in the crypto asset market is limited, despite crypto assets receiving considerable attention in policy circles. To the best of our knowledge, (Delias et al., 2022) is the only study that provides experimental evidence on the impact of the salience and content of risk warnings on consumers' comprehension and perception of key risks for crypto assets. We contribute to this strand of the literature by evaluating the impact of behaviorally informed risk warnings in an environment that mimics the real world more closely (see Section 5.4 for details).

3.2 Type of Information

Information disclosures serve as essential regulatory mechanisms designed to mitigate information asymmetries between investors and product providers, thereby empowering individuals to make well-informed decisions. On the one hand, various behavioral and experimental studies have shown that risk preferences and financial decisions can be influenced by the simple presentation of information (Kahneman and Tversky, 1974, 1979; Tversky and Kahneman, 1981; Weber et al., 2005; Vlaev et al., 2009; Wang et al., 2011; Linciano et al., 2018). On the other hand, it is shown that information disclosures must be not only simple (Wilcox, 2003; Beshears et al., 2009; Barber et al., 2005) but also salient—that is, they should be noticeable, capable of capturing attention, and perceived as significant in the decision-making process (Desanctis and Jarvenpaa, 1989; Wang et al., 2011; Weathers et al., 2012). We contribute to this strand of literature by providing risk warnings that are both simple and salient, informed by behavioral economics. The behavioral concept used in our study is related to loss aversion, which refers to the tendency for individuals to prefer avoiding losses over acquiring equivalent gains (Tversky and Kahneman, 1992). By integrating insights from behavioral economics, our approach aims to enhance the effectiveness of risk warnings in high-risk investments (Delias et al., 2022), ultimately supporting better-informed financial decisions among consumers.

3.3 Order of Information

The order in which information is presented in financial contexts plays a crucial role in shaping investor decision-making, often due to cognitive biases like primacy and recency effects (Hogarth and Einhorn, 1992). The primacy effect suggests that investors give disproportionate weight to the information presented first, which can lead to initial impressions heavily influencing overall assessments. Conversely, the recency effect indicates that information presented last is more likely to be remembered and deemed significant (Mulligan and Hastie, 2005; Hellmann et al., 2017). Experimental evidence by (Aprayuda et al., 2021) shows that investors who received negative information followed by positive information valued investments higher than those who received the information in the opposite order. (Daigle et al., 2015) finds that initial primacy effects revert to recency effects over time in a market setting with economic incentives, affecting nonprofessional investors' stock price valuation decisions. We extend this body of literature by implementing two distinct treatment arms: one where risk warnings are presented before returns and another where risk warnings follow returns. This approach allows us to assess whether the primacy or recency effect of risk warnings is more effective in enhancing risk comprehension and perceptions of investments in crypto assets.

3.4 At-Risk Investors

In our heterogeneity analysis, we focus on a specific subgroup of participants that we define as "at-risk investors." We define this at-risk group as individuals who follow crypto market updates on social media but have not yet invested in crypto assets. The decision to investigate heterogeneity within this group is motivated by recent literature suggesting that risk tolerance among investors can increase when they follow market trends and updates, particularly during periods of high market returns (Mirtaheri et al. (2021); Kawai et al. (2023). This heightened risk tolerance can lead them to perceive high-risk products as potentially lucrative investments (Yao and Curl, 2011). Additionally, individuals who frequently assess high-risk investments adjust their risk perceptions over time, often becoming more comfortable with the associated risks. This increased comfort can subsequently make them more likely to invest in high-risk investments (Tversky and Fox, 1995; Khang, 2012; Newall and Weiss-Cohen, 2022). Therefore, it is crucial to determine if risk warnings are effective for this specific group. Understanding the impact of risk warnings on these at-risk investors can inform the design of targeted interventions and policies aimed at protecting them from potentially detrimental investment decisions.

4 Stylised Facts

4.1 Crypto Asset Ownership

The ownership of crypto assets is characterized by a diverse demographic with varying motivations. Generally, crypto asset investors tend to be young, well-educated, and predominantly male (Weber et al., 2023; Campino and Yang, 2024). They are often digital natives, comfortable with online financial tools, and frequently exhibit higher levels of financial literacy (Auer and Tercero-Lucas, 2022; Steinmetz et al., 2021), risk tolerance (Pelster et al., 2019; Fujiki, 2020), and income levels (Aiello et al., 2023). In Ireland, 36% of adults have an investment product (CCPC, 2021) and 16% have either used or owned some kind of crypto assets (Statista, 2023).[6] Given that a majority (62%) of people in Ireland rely online to seek information about investing from blogs, social media, investment websites, etc. (CCPC, 2021), this makes our study population potentially vulnerable as information available on social media can influence investment decisions despite its low-quality nature (Kadous et al., 2024).

4.2 Regulatory Environment

Regulatory warnings by supervisory authorities play a crucial role in the crypto assets ecosystem. These warnings aim to help mitigate risks associated with the volatile nature of crypto assets. Governments and regulatory bodies have issued various advisories highlighting the potential dangers of investing in digital assets, such as the risks of money laundering, fraud, and market manipulation. Similarly, the European Securities and Markets Authority (ESMA) warns that the asset class is extremely risky and has also issued requirements for 'finfluencers' and others who post investment recommendations on social media (ESMA, 2024a,b, 2022).

In Ireland, the Central Bank of Ireland (CBI) has issued warnings highlighting the high risks associated with crypto assets, including their volatility, lack of consumer protection, and potential for loss (CBI, 2022, 2024a). These warnings are part of a broader strategy to educate the public and mitigate the risks of financial instability. Additionally, the introduction of the Markets in Crypto Assets Regulation (MiCAR) further aims to protect consumers and investors and mitigate risks to financial stability.[7]

5 Methodology & Experimental design

5.1 Recruitment Strategy

Participants for this online experiment were recruited through an online panel provider (redcresearch.com) and were only identifiable using a randomly generated ID number.

[6] Many large online shops and even some high-street chains now let customers pay in Bitcoin or other tokens at checkout (e.g., Microsoft, Starbucks) (Capital One Shopping Research Team, 2024). Savers park spare cash in euro or dollar-pegged stablecoins because the main crypto apps currently pay roughly 5–8% interest or "staking" rewards on these balances, which is well above a typical bank account (Barker, 2025). And migrant workers increasingly use crypto wallets for remittances, trimming average transfer costs from the 5–7% charged by traditional providers to about 1–2% (Elad, 2024). In short, ordinary users are starting to pay, save, and send with crypto, not just speculate.

[7] MiCAR brings issuers of certain types of crypto assets into the regulatory framework. MiCAR became applicable for issuers of Asset-Reference Tokens and issuers of E-Money Tokens on 30 June 2024. Specifically, MiCAR establishes new rules for issuers of crypto assets known as 'stablecoins', including ARTs, EMTs, along with new rules for utility tokens (CBI, 2024b). See (EU, 2023) for details.

No personally identifiable information was collected from them during the online trial. Participants were not explicitly informed about the purpose of the experiment, nor were they made aware that different investment browsing experiences were being tested. Participation was entirely voluntary, and participants could exit from the experiment at any stage. Informed consent was obtained from every participant before the start of the online survey, and only those who agreed to be surveyed became part of the online experiment. We constructed the sample for this experiment to be representative of the general population of Ireland (IRE) to maximize the external validity of our experimental findings. This included constructing the sample to reflect the gender, age, social grade, and regional location profile of people living in Ireland.

5.2 External Validity

To assess the representativeness of our sample, we compare summary statistics of our sample to the population of Ireland. Table 1 compares mean proportions between our sample (N=2005) and the demographic data provided by the Central Statistics Office (CSO) and the Association of Irish Market Research Organizations (AIMRO). The comparison reveals several minor discrepancies. For instance, our sample has a higher percentage of females (59%) compared to the population (51%), and a lower percentage of males (41%) compared to the population (49%). The age distribution also shows under-representation of the 18-24 age group (6% vs. 14%) and over-representation of the 35-44 (33% vs. 25%) and 45-54 (25% vs. 22%) age groups. Additionally, the sample over-represents the higher social grades AB (20% vs. 12%) and under-represents the lowest social grade F (2% vs. 6%). Regional representation is relatively accurate, with minor discrepancies such as slight under-representation in Dublin (26% vs. 29%) and over-representation in Ulster/Connacht (19% vs. 17%).

To address these minor discrepancies and enhance external validity, we employ an approach that involves adjusting the sample proportions to match the population distribution for gender, age, social grade, and region. Specifically, gender and age-specific weights can correct for the under-representation of males and younger age groups. In contrast, social grade weights can adjust for the over-representation of higher social grades. Although regional discrepancies are minor, applying regional weights can further improve accuracy. These adjustments will ensure that our sample better reflects the population, thereby enhancing the generalizability of our findings. Applying sample weights does not change the results we discuss in this paper.

Table 1. External Validity: Population & Sample Proportions

		Population (2023)	Sample (N=2005)
Gender	Male	49%	41%
	Female	51%	59%
Age	18-24	14%	6%
	25-34	20%	17%
	35-44	25%	33%
	45-54	22%	25%
	55-64	20%	20%
	65+	20%	
Social Grade	AB	12%	20%
	C1	34%	37%
	C2	20%	21%
	DE	28%	19%
	F	6%	2%
Region	Dublin	29%	26%
	Rest of Leinster	27%	27%
	Munster	27%	28%
	Ulster/ Connacht	17%	19%

Notes: Table reports mean proportions for the whole population and our sample. Population statistics for gender, age, and region are borrowed from the Central Statistics Office of Ireland (CSO), whereas statistics for social class are provided by the Association of Irish Market Research Organizations (AIMRO).

5.3 Intervention

Participants were asked to go through a fictitious investment browsing experience. They were presented with two mock-ups of financial promotions, each displaying a different investment product, and had to view both to continue with the experiment. The first product was always stocks and always included a standard ‘Your capital is at risk’ warning. The second product was a high-risk investment, namely crypto assets with a behaviorally informed risk warning and information about crypto asset market returns, volatility, or neutral information depending on the treatment arm. Once participants had browsed through both investment options, they were asked several questions on their risk comprehension and perception, and the extent to which they would recommend the investments in stocks and crypto assets to a hypothetical friend.

5.4 Treatment Assignment

We recruited a sample of 2,005 individuals from a participant pool representative of the Irish population. As shown in Figure 2, participants were randomly assigned to one of four groups: a control group (N = 502) or one of three treatment groups: Treatment 1 (Warnings + Returns, N = 502), Treatment 2 (Returns + Warnings, N = 501), and Treatment 3 (Warnings + Volatility, N = 500). All participants were shown investment advertisements for both stocks and crypto assets. In every group, the risk warning accompanying the stock promotion remained standard and unaltered. In contrast, the risk warnings associated with the crypto asset promotion varied by group: the control group received the standard risk warning, while all treatment groups received a behaviourally informed risk warning designed to increase risk salience. Treatment groups additionally received either past return information or price volatility cues related to crypto assets, depending on the group.

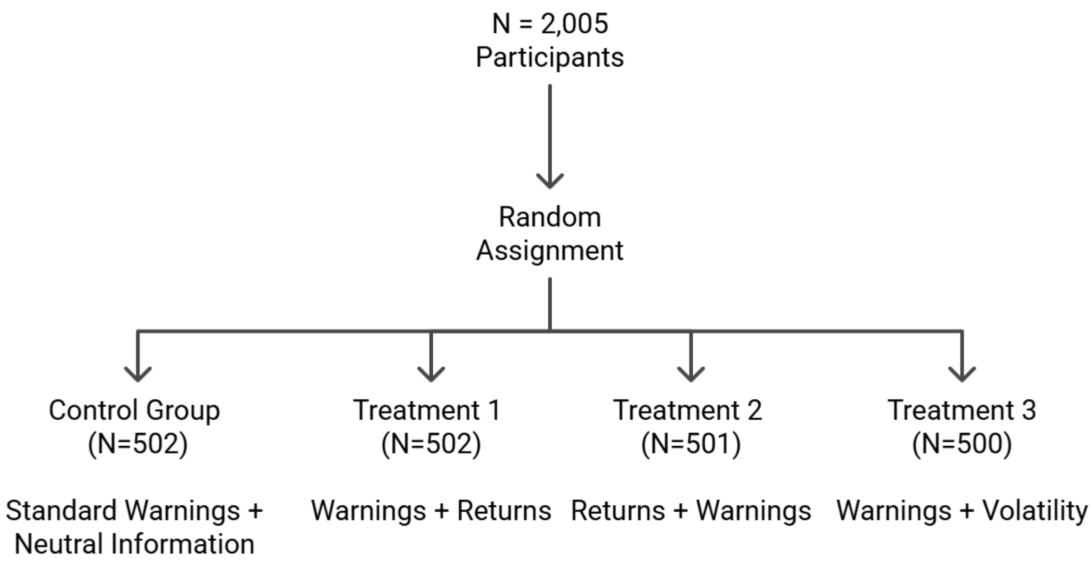


Figure 2. Randomisation & Treatment Assignment

1. **Control:** Participants in the control group saw the advertisement on stocks with a standard 'Your capital is at risk' warning, followed by an advertisement on crypto assets with a standard 'Your capital is at risk' warning, and lastly some neutral information about investment scams and the Irish labor market. Given that other treatment arms receive information about crypto asset returns or volatility, providing the control group with neutral information controls for the act of giving information across treatment arms. This group serves as our main comparison group and allows us to measure the combined effect of introducing both returns and risk warnings, relative to a low-salience baseline. Figure A1 in the Appendix

details the investment browsing experience of participants randomly assigned to the control group.

2. **Warnings + Returns:** Participants in this treatment group saw the advertisement on stocks with a standard 'Your capital is at risk warning' and a behaviorally informed risk warning for crypto assets. The behaviourally informed risk warning tested in this experiment revolves around the concept of loss aversion and was shown to be quite effective in improving risk comprehension in the experiment by The Financial Conduct Authority (Delias et al., 2022). After the warnings, participants are also shown information about the amount of returns they would have made if they had invested in crypto assets five years ago. Figure A2 details the investment browsing experience of participants randomly assigned to the (Warnings + Returns) group.

3. **Returns + Warnings:** This treatment group is exactly the same as the previous one, with the only difference being that the order of the information is now reversed. Instead of showing participants risk warnings before crypto market returns, we show them warnings after crypto market returns. The reverse order of information in this treatment arm will help us evaluate the impact of the order of the information. Figure A3 details the investment browsing experience of participants randomly assigned to the (Returns + Warnings) group.

4. **Warnings + Volatility:** Participants in this treatment group saw the advertisement on stocks with a standard 'Your capital is at risk warning' and a behaviorally informed risk warning for crypto assets similar to those in treatment groups 2 and 3. Additionally, participants were provided with explicit information about the extreme volatility of crypto markets. This combination of behaviorally informed risk warnings with insights into crypto market volatility aims to amplify the salience of investment risks. By reinforcing the uncertainty and potential losses associated with crypto assets, this approach aimed to heighten participants' awareness of the dangers involved in investing in crypto assets. Figure A4 details the investment browsing experience of participants randomly assigned to the (Warnings + Volatility) group.

In designing this experiment, our objective was to evaluate the impact of behaviourally informed risk warnings in a setting that mirrors how retail investors typically encounter crypto asset promotions. In practice, such promotions often combine attention-grabbing historical returns with a standardised disclaimer (e.g., "Your capital is at risk"), which may downplay the true risks involved. To replicate this environment, all three treatment arms include a behaviourally informed risk warning. What differs across treatments is the additional information shown alongside the warning: in Treatment 1, the warning is followed by historical return information (framed positively); in Treatment 2, the order is reversed, with the warning shown before the returns; and in Treatment 3, the warning is paired with price volatility cues rather than returns. The control group includes only the standardised risk warning and neutral, unrelated information.

This design choice allows us to measure the combined effect of introducing both returns and risk warnings, relative to a low-salience baseline. As such, our treatment effect does not isolate the impact of the behavioural warnings, returns, or volatility cues alone, but captures the net impact of replacing a minimal, generic disclosure with a more realistic, promotion-style intervention. This aligns with the type of decision regulators face when considering whether to enhance current disclosure rules in environments where crypto ads already emphasize high returns. We did not add return information in our control to establish a neutral baseline. While this deviates from how crypto products are often marketed in practice, it allows us to interpret the treatment effect as the combined impact of showing returns and embedding a behaviourally informed risk warning, relative to a low-salience baseline. Future work could decompose these effects by including return information in both control and treatment arms.

6 Sample & Data

6.1 Sample Description

Prior to the main survey, a pilot study was conducted from December 15th to 18th, 2023. The findings from this pilot were instrumental in refining the survey further. Additionally, the pilot data was used to do a power analysis for our three primary outcomes. The power analysis indicated that with 501 participants per treatment arm, or 1,000 participants per hypothesis, we would have sufficient power to detect effects of 5.66%, 3.5%, and 10.82% for risk comprehension, risk perception, and the likelihood of recommending crypto assets to a friend, respectively. The full survey data was collected from December 20th, 2023, to January 19th, 2024. This period includes days when data collection was paused due to Christmas Eve and New Year's holidays. We examined whether the responses collected before these holidays differed from those collected afterward and found no statistically significant differences.

Table 2. Descriptive Statistics Across Treatment Groups

	Full Sample	Control	T1 (W+R)	T2 (R+W)	T3 (W+V)
Dublin	0.261	0.299	0.255	0.246	0.246
Age ≤ 34	0.225	0.233	0.249	0.218	0.202
Male	0.413	0.388	0.442	0.403	0.418
Third Level Education	0.661	0.649	0.643	0.661	0.692
Employed at the time of Interview	0.749	0.753	0.737	0.745	0.760
Income $>$ €49,000	0.323	0.341	0.267	0.331	0.354
Financial Literacy Score (%)	72.231	71.735	70.031	73.320	73.844
Digital Products Use (%)	41.932	41.633	41.271	41.027	43.800
Financial Products Use (%)	47.756	48.008	46.315	46.682	50.025
Investment Experience (years)	2.696	2.669	2.497	2.327	3.290
Ever Invested in Crypto Assets	0.150	0.124	0.151	0.160	0.164
Follow Crypto Updates on Media	0.634	0.665	0.606	0.653	0.612
Risk Lover	0.181	0.185	0.159	0.202	0.178
Observations	2005	502	502	501	500

Notes: Table reports means of demographic, financial, and personality characteristics first for the whole sample and then for each study group. Age, male, third level education, employed, income, every invested in crypto assets, ever considered investments in crypto assets, follow crypto updates, and risk lover are binary variables that take the value of one for the stated category and 0 otherwise. Financial literacy score, digital product use, and financial product use are continuous variables expressed in percentage terms, whereas investment experience is expressed in years.

Our final sample consists of 2,005 respondents, representing the Irish population. As there were no incomplete or duplicate responses, this sample also serves as our estimation sample, equally divided between the control group (25%) and the three treatment groups (25% each). Table 2 reports summary statistics for a variety of demographic and financial variables in our data. Around 26% of the respondents in our sample live in Dublin, and 22% are less than or equal to 34 years of age. The average respondent in our data has 2.69 years of investment experience, and 15% said yes to ever investing in crypto assets. The average financial literacy score at baseline is 72%, while the digital product use score and financial product use score are 42% and 48% among our respondents.[8] It's noteworthy how, despite only 15% of respondents answering yes to ever investing in crypto assets, a significant majority (63%) follow crypto asset updates on social media. This makes a significant proportion of our sample vulnerable to low-quality investment advice on social media (Kadous et al., 2024).

8 Financial literacy score is calculated from a set of eight questions that gauge participants' understanding of concepts such as inflation, interest rates, compounding, volatility, and diversification in investments. The digital and financial products score is derived from a series of binary questions asking respondents whether they use specific financial and digital products. A 40% score indicates that, on average, participants use 40% of the digital and financial products presented.

6.2 Baseline Balance

To check balance between treatment arms, Table 3 compares the control group's mean with means in each of our three treatment arms. Out of 39 comparisons (13 outcomes x 3 treatment groups), we find statistically significant differences for 8 comparisons. However, the joint significance test reveals equality of means for T2 and T3 and only a weak statistically significant difference for T1. Since any differentials between treatment and control may lead to an under- or over-estimation of treatment effects, we include imbalance variables (region, gender, income, digital product use, ever invested in crypto assets, and follow crypto asset updates on media) as covariates in our primary specification.

7 Empirical strategy

7.1 Outcomes

Our outcomes of interest are divided into two main categories: primary and secondary. Table 4 shows the primary and secondary outcomes used in this paper. Our primary outcomes consist of: (i) Risk Comprehension (Crypto Assets) which is measured on a continuous scale and is expressed in percentage terms (range: 0-100); (ii) Risk perception for stocks and crypto assets, measured on a continuous scale (range 1-10); and (iii) two binary variables indicating recommendation of stocks and crypto assets to a hypothetical friend. We define risk comprehension as consumers' awareness regarding the maximum loss possible and the amount of protection they can expect if things go wrong after they have invested in crypto assets. Risk perception is defined as the ability of investors to understand when an investment is risky. Crypto asset recommendations measure the likelihood that individuals would advise a hypothetical friend to allocate some of their savings to crypto assets. Following (Berger, 2014), we use this as a proxy for participants' actual attitudes toward investing, under the assumption that recommending an investment to a friend carries significant implications for one's investment attitudes. Our secondary outcomes include 4 likert style variables (range 1-7) indicating a willingness to sell (or hold) a losing (or winning) investment, with higher values meaning more willingness to hold and lower values measuring more willingness to sell. We ask this separately for stocks and crypto assets. See Table A1 in the Appendix for details on how each measure was constructed.

Table 3. Test of Covariate Balance by Treatment Arm

	(1) Control Mean	(2) T1 - C	(3) T2 - C	(4) T3 - C
Dublin	0.299	–0.044	–0.053*	–0.053*
	(0.020)			
Age $\leq$ 34	0.233	0.016	–0.016	–0.031
	(0.019)			
Male	0.388	0.054*	0.015	0.030
	(0.022)			
Third Level Education	0.649	–0.006	0.011	0.043
	(0.021)			
Employed at the time of Interview	0.753	–0.016	–0.008	0.007
	(0.019)			
Income $>$ €49,000	0.341	–0.074**	–0.009	0.013
	(0.021)			
Financial Literacy Score (%)	71.735	–1.704	1.585	2.109
	(1.036)			
Digital Products Use (%)	41.633	–0.362	–0.606	2.167**
	(0.704)			
Financial Products Use (%)	48.008	–1.693	–1.326	2.017
	(0.903)			
Investment Experience (years)	2.669	–0.172	–0.342	0.621
	(0.276)			
Ever Invested in Crypto Assets	0.124	0.028	0.036	0.040*
	(0.015)			
Follow Crypto Updates on Media	0.665	–0.060**	–0.013	–0.053*
	(0.021)			
Risk Lover	0.185	–0.026	0.016	–0.007
	(0.017)			
F-test of joint significance (F-stat)		1.534*	1.015	1.361
Number of observations	502	1004	1003	1002

Notes: This table reports means and standard deviations in parentheses of demographic, financial, and personality characteristics for the control group. Columns (2), (3), and (4) shows balance across treatment arms for a battery of demographic, financial and personality characterstics; F-test of joint significance tests the joint significance of the full set of coefficients from a linear regression of the balance variables on a treatment indicator estimated on the subsample including the two relevant groups. ***, **, and * indicate significance at 1, 5, and 10 percent critical levels.

Table 4. Primary and Secondary Outcomes

Outcome	Nature	Scale	Label
Risk Comprehension (Crypto)	Primary	Continous score (%)	RC Crypto (%)
Risk Perception (Stocks)	Primary	Continous score (1-10)	RP Stocks (1-10)
Risk Perception (Crypto)	Primary	Continous score (1-10)	RP Crypto (1-10)
Recommendation (Stocks)	Primary	=1 if Recommend Stocks	Rec Stocks (1/0)
Recommendation (Crypto)	Primary	=1 if Recommend Crypto	Rec Crypto (1/0)
Willingness to Hold (Losing Stock)	Secondary	Continous score (1-7)	WHS Losing
Willingness to Hold (Winning Stock)	Secondary	Continous score (1-7)	WHS Winning
Willingness to Hold (Losing Crypto)	Secondary	Continous score (1-7)	WHC Losing
Willingness to Hold (Winning Crypto)	Secondary	Continous score (1-7)	WHC Winning

Notes: This table reports primary and secondary outcomes used in this paper. For risk comprehension and perception, higher values mean more comprehension and perception, respectively. Recommendation variables are binary, with 1 representing the likelihood of recommending either stocks or crypto assets to a hypothetical friend. For willingness to hold, higher values mean more willingness to hold, whereas lower values mean more willingness to sell. For details on how these variables were measured and construed, see Table A1 in the Appendix of this paper.

7.2 Estimation

Our parameter of interest in this study is the Intent-To-Treat (ITT) estimate of the Average Treatment Effect (ATE) of offering risk warnings, returns, and volatility information on risk comprehension, risk perception, and retail investment behaviour. We obtain the parameter estimate $\hat{\tau}$ by estimating the following specification, using OLS, on the full sample:

$$Y_i = \alpha + \tau_1 T_i^{W+R} + \tau_2 T_i^{R+W} + \tau_3 T_i^{W+V} + X_i + \varepsilon_i \quad (1)$$

Y_i denotes the outcome for individual i. Assignment to the (Warnings+Returns) group is denoted by the indicator T_i^{W+R}. Similarly, assignment to the (Returns+Warnings) and (Warnings+Volatility) groups is denoted by the indicators T_i^{R+W} and $T^{W+V}i$, respectively. Xi refers to a set of standard controls, which include age, region, gender, a binary variable for income above €49,000, a digital product use score, a dummy variable indicating whether the respondent follows crypto market updates on social media, and a dummy variable indicating whether the respondent has ever invested in crypto assets.[9] Lastly, ε_i denotes an idiosyncratic error term. The impact estimates are identified due to random assignment to treatment at the individual level. For our primary and secondary outcomes, we report both standard p-values and False Discovery Rate-adjusted p-values, using the step-down bootstrap algorithm provided by Romano et al. (2010). The adjusted p-values are based on 1,000 bootstrap replications.

7.3 Treatment Effect Heterogeneity

Next, we test whether some participants respond to our treatments more strongly than others. This exercise investigates whether the overall effectiveness of our treatment, especially in improving risk comprehension and risk perception, is driven by a particular subgroup. To do this, we estimate the following model with interaction terms between the treatment variable and the characteristics of interest:

$$Y_i = \alpha + \tau_1 T_i^{W+R} + \tau_2 T_i^{W+R} \times X_i + \tau_3 T_i^{R+W} + \tau_4 T_i^{R+W} \times X_i + \tau_5 T_i^{W+V} + \tau_6 T_i^{W+V} \times X_i + \varepsilon_i \quad (2)$$

In the equation above, τ_1, τ_3, and τ_5 refer to the average treatment effect for the base category for the three treatment arms (i.e., the category which is coded as zero). Similarly, τ_2, τ_4, and τ_6 refer to the interaction term for each of the treatment arms, and

9 The threshold of €49,000 is chosen because it corresponds to the median annual income in Ireland, based on 2022 figures published by the Central Statistics Office (CSO).

X_i refers to the heterogeneity variable of interest. To calculate the average treatment effect for the category that is coded as one, we add the treatment effect for the base category to the interaction term coefficient. We focus on two sources of heterogeneity in this paper. The first is At-Risk Investors, a binary variable that takes the value of 1 for individuals who follow crypto asset updates on social media but have not yet invested in them. The second is Ever Invested in Crypto Assets, a binary variable that equals 1 for individuals who have previously invested in crypto assets. These two groups allow us to explore how prior exposure to or engagement with crypto assets might moderate the effects of our interventions. As shown in Table 5, 59% of the sample is classified as at-risk, while 15% have invested in crypto assets in the past.

Table 5. Summary Statistics Heterogeneity Groups

	Sample	Control	T1 (W+R)	T2 (R+W)	T3 (W+V)
Ever Invested in Crypto Assets	0.150	0.124	0.151	0.160	0.164
Follow Crypto Updates on Media	0.634	0.665	0.606	0.653	0.612
At-Risk Investor (Follow but Not Invest)	0.585	0.622	0.562	0.589	0.566
Observations	2005	502	502	501	500

Notes: Table reports means of sample characteristics for the whole sample and for each study group. Ever invested in crypto assets and follow crypto updates on media are binary variables that take the value of one for the stated category and 0 otherwise. At-Risk is a binary variable that takes the value of 1 for respondents who follow crypto asset updates on media but haven't ever invested in crypto assets yet and 0 otherwise. The respondents in the zero category for At-Risk are those who have invested in crypto assets or those who do not follow crypto asset updates on social media.

8 Results

In this section, we examine the treatment effects on our primary and secondary outcomes before concluding with a section on heterogeneous treatment effects.

8.1 Risk Comprehension

Table 6 presents the impact of behaviorally informed risk warnings and information order on our primary outcomes. The average risk comprehension score is 68% in the control group. This is increased by 3.1 percentage points (pp) or 5% (p-value < 0.1; FWER p-value > 0.1) for the treatment group who were shown warnings before returns. Changing the order of information, i.e., showing respondents warnings after returns, leads to an 8.0 pp (or 12%) increase in risk comprehension relative to the control group (p-value < 0.01; FWER p-value < 0.01). Comparing the coefficients of treatment groups 1 and 2 reveals statistically significant differences (p-value = 0.004), suggesting that the order of information matters for improvements in risk comprehension. The treatment involving warnings and volatility information leads to an improvement of 6.3 pp or 9% over a mean of 68% in the control group (p-value $<$ 0.01; FWER p-value $<$ 0.01). Comparing the coefficients of treatment groups 1 and 3 reveals statistically significant differences (p-value = 0.054). It is possible that showing respondents warnings and volatility cues increases the salience of risk, as both elements emphasize the uncertain and unstable nature of crypto assets. This heightened salience may explain the observed improvement in risk comprehension (by 4%) relative to treatment group one, which received only warnings and returns information.

8.2 Risk Perception

Columns (2) and (3) in Table 6 present the impact of behaviorally informed risk warnings and information order on risk perception for stocks and crypto assets. The average risk perception score for stocks in the control group is 6.5 points on a 10-point scale. We find a reduction in risk perception for stocks across all treatments (0.1% to 2.8%), but this is not statistically significant (p-value $>$ 0.1). This finding is in line with (Delias et al., 2022), which suggests that improvements in risk perception for crypto assets may make people perceive stocks as less risky. The statistically insignificant nature of these treatment effects is not surprising because all treatments were focused on informing respondents about the high-risk nature of crypto assets, whereas stocks were only presented with a standard 'your capital is at risk warning' and were shown to all study groups.

The average risk perception score for crypto assets in the control group is 8.2 on a 10-point scale. This increases by 0.32 points (or 4%) for the treatment group that was shown risk warnings before returns (p-value $<$ 0.01; FWER p-value = 0.1). Changing the order of information results in a 0.46 point increase (or 6%) in risk perception relative to the control group (p-value $<$ 0.01; FWER p-value $<$ 0.01). Comparing coefficients between treatment groups 1 and 2 shows that presenting warnings before returns leads to a further 2% increase in risk perception; however, this difference is not statistically significant (p-value = 0.270). The treatment involving warnings and volatility information leads to a 0.57 point increase (or 7%) relative to the control group (p-value $<$ 0.01; FWER p-value $<$ 0.01). Comparing treatment groups 1 and 3 provides statistically significant evidence of increased salience of risk: risk perception improves by a further 2% relative to treatment group 1, similar to the pattern observed for risk comprehension (p-value = 0.032). These treatment effects are meaningful given the already high control group mean of 8.2 on a 10-point scale.

8.3 Investment Recommendation

Columns (4) and (5) in Table 6 present the impact of behaviorally informed risk warnings and the order of information on the likelihood of recommending stocks and crypto assets to a hypothetical friend. The average stock recommendation in the control group is 39%. Providing respondents with warnings before returns increases this by 3.3 percentage points (pp) (or 9%) relative to the control group (p-value > 0.1; FWER p-value > 0.1). Changing the order of information significantly increases stock recommendations by 5.2 pp (or 13%) relative to the control group (p-value < 0.1; FWER p-value > 0.1). Notably, simply changing the order of information results in a statistically insignificant treatment effect of 9%, which increases by a further 4% to 13% and becomes significant (p-value < 0.1). We observe similar patterns for the group with warnings and volatility information, where stock recommendations significantly increase by 6.0 pp (or 15%). Overall, there is a positive increase in stock recommendations across all treatments. This could be linked to a decreased perception of risk for stocks due to our treatments, making respondents perceive stocks as less risky and therefore more likely to recommend them to their friends (Delias et al., 2022).

The average crypto asset recommendation in the control group is 15%. We find an increase of 5% for the group that received warnings before returns and a decrease of 7% for the group that received warnings after returns relative to the control group. However, both of these point estimates are statistically insignificant. Despite being statistically insignificant, changing the order of information alters both the direction and magnitude of the point estimate, suggesting the importance of information order in our context. For the group that received warnings and volatility information, crypto asset recommendations decreased by 2.2 pp (or 15%) relative to the control group (p-value $>$ 0.1; FWER p-value > 0.1). The lack of statistical significance across the three treatments could be attributed to the low baseline value of the control group, where the average crypto recommendations are already very low at 15%, indicating the presence of a floor effect.

Table 6. Treatment Effect on Primary Outcomes

VARIABLES	(1) RC Crypto (%)	(2) RP Stocks (1-10)	(3) RP Crypto (1-10)	(4) Rec Stocks (1/0)	(5) Rec Crypto (1/0)
T1: Warnings + Returns	3.121*	-0.171	0.327***	0.033	0.008
	(1.766)	(0.130)	(0.120)	(0.030)	(0.022)
T2: Returns + Warnings	7.889***	-0.007	0.458***	0.052*	-0.011
	(1.662)	(0.132)	(0.119)	(0.031)	(0.022)
T3: Warnings + Volatility	6.357***	-0.185	0.571***	0.060**	-0.022
	(1.646)	(0.127)	(0.115)	(0.031)	(0.022)
Observations	2,005	2,005	2,005	2,005	2,005
Mean Control	67.73	6.536	8.243	0.388	0.155
TE T1 %	4.609	-2.621	3.964	8.578	4.976
TE T2 %	11.65	-0.112	5.550	13.49	-7.061
TE T3 %	9.386	-2.831	6.925	15.54	-14.29
T1=T2 (p-value)	0.004	0.227	0.270	0.534	0.405
T1=T3 (p-value)	0.054	0.917	0.032	0.382	0.184
T2=T3 (p-value)	0.333	0.182	0.316	0.798	0.603
Romano-Wolf [p-values]					
T1: Warnings + Returns	.576	.576	.100	.576	.576
T2: Returns + Warnings	.000	.995	.000	.220	.995
T3: Warnings + Volatility	.000	.278	.000	.051	.707

Notes: This table reports OLS estimates of treatment effects. Controls include age, region, gender, a binary variable for income above €49,000, a digital product use score, a dummy variable indicating whether the respondent follows crypto market updates on social media, and a dummy variable indicating whether the respondent has ever invested in crypto assets. Columns 1-5 show results for our primary outcomes; risk comprehension expressed in percentage terms, risk perception for stocks and crypto assets expressed as ordinal variables with higher values meaning more risk perception and finally two binary variables which take the value of 1 if the respondent would like to recommend stocks or crypto assets to a hypothetical friend and zero otherwise. For each outcome variable, we report the coefficients of interest and their robust standard errors in parentheses. We also report treatment effects expressed in percentage terms, p-values for equality of coefficients across treatment arms, and FWER-correct p-values for each outcome following the methodology proposed by (Romano et al., 2010) based on 1,000 replications. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels. Coefficients for the control variables used in these regressions are not shown here for brevity but are reported in Table A2.

8.4 Willingness to Hold / Sell Investments

The tendency of individuals to sell assets that have increased in value too quickly, while holding onto assets that have decreased in value, is a well-documented cognitive bias in behavioral finance. This phenomenon, known as the disposition effect, was first observed by Shefrin and Statman (1985) and is often linked to investors' inherent aversion to losses (Kahneman, 2013). Previous work in this space has shown that loss aversion among investors can vary with market conditions (Hwang and Satchell, 2010), making it particularly relevant in crypto asset markets, which frequently experience multiple bull and bear cycles within a single year. We hypothesize that behaviorally informed risk warnings may influence individuals' decisions to hold or sell winning and losing investments by altering their risk comprehension and perception.

In Table 7, we present the impact of behaviorally informed risk warnings and information on retail investment behavior. Specifically, we examine the effect of treatment on the willingness to hold stocks and crypto assets. Columns (1) and (2) report impact estimates on the willingness to hold winning and losing stocks, while Columns (3) and (4) present the corresponding estimates for winning and losing crypto assets. Across all treatments, and for both stocks and crypto assets, we observe a reduction in the willingness to hold both winning and losing investments. This can be interpreted as a decrease in the disposition effect (Lisauskiene et al., 2023). We attribute this to improvements in risk comprehension and perception, particularly about crypto assets. These findings align with experimental evidence from Döbrich et al. (2014), who observed reductions in the disposition effect following rational and emotional warnings in a simulated stock market environment. However, most impact estimates, while negative in magnitude, are not statistically significant except for the willingness to hold a winning crypto asset for the treatment group that was shown warnings and volatility information. For this treatment group, we find a statistically significant decrease (p-value < 0.05) of 0.3 points (or 8%) on a 7-point scale relative to the control mean of 3.82.

Table 7. Treatment Effect on Secondary Outcomes

VARIABLES	(1) WHS Losing	(2) WHS Winning	(3) WHC Losing	(4) WHC Winning
T1: Warnings + Returns	-0.168	-0.102	-0.187	-0.030
	(0.113)	(0.125)	(0.116)	(0.122)
T2: Returns + Warnings	-0.034	-0.014	-0.089	0.027
	(0.115)	(0.125)	(0.118)	(0.124)
T3: Warnings + Volatility	-0.039	-0.152	-0.048	-0.302**
	(0.116)	(0.127)	(0.121)	(0.125)
Observations	2,005	2,005	2,005	2,005
Mean Control	4.217	4.327	3.659	3.821
TE T1 %	-3.988	-2.359	-5.121	-0.793
TE T2 %	-0.808	-0.323	-2.431	0.710
TE T3 %	-0.922	-3.511	-1.324	-7.895
T1=T2 (p-value)	0.249	0.480	0.400	0.640
T1=T3 (p-value)	0.274	0.693	0.250	0.028
T2=T3 (p-value)	0.968	0.278	0.740	0.009
Romano-Wolf [p-values]				
T1: Warnings + Returns	0.342	0.588	0.342	0.880
T2: Returns + Warnings	0.996	0.996	0.951	0.996
T3: Warnings + Volatility	0.999	0.536	0.999	0.052

Notes: This table reports OLS estimates of treatment effects. Controls include age, region, gender, a binary variable for income above €49,000, a digital product use score, a dummy variable indicating whether the respondent follows crypto market updates on social media, and a dummy variable indicating whether the respondent has ever invested in crypto assets. Columns 1-4 show results for our secondary outcomes. WHS and WHC stand for willingness to hold or sell a stock or crypto asset on a scale of 1-7, where higher values mean more willingness to hold and lower values mean more willingness to sell. We report WHS and WHC for both losing and winning stocks and crypto assets. For each outcome variable, we report the coefficients of interest and their robust standard errors in parentheses. We also report treatment effects expressed in percentage terms, p-values for equality of coefficients across treatment arms, and FWER-correct p-values for each outcome following the methodology proposed by (Romano et al., 2010) based on 1,000 replications. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels. Coefficients for the control variables used in these regressions are not shown here for brevity but are reported in Table A3.

8.5 Heterogeneity: At-Risk Investors

In Table 8, we present impact estimates for the at-risk investors group for our primary and secondary outcomes.[10] We define this at-risk group as individuals who follow crypto market updates on social media but have not yet invested in crypto assets.

Column (1) in Table 8 presents the impact of behaviorally informed risk warnings and information order on risk comprehension for crypto assets. The average risk comprehension score for the control at-risk group is 70%, whereas for the control non-at-risk group, it's 63%. Across all treatment groups, we find significant improvements in risk comprehension for the group that is at-risk. Changing the order of information improves the treatment effect from 7% (4.893 / 70.35) for the warnings before returns group to 12% (8.544 / 70.35) for the warnings after returns group. Similarly, increasing the salience improves the treatment effect from 7% for the warnings before returns group to 9% for the warnings plus volatility group. We find similar patterns for risk perception for crypto assets where the treatment effect improves from 6% for the warnings before returns group to 7% for the warnings after returns groups and to 8% for the warnings plus volatility group. We believe these point estimates to be meaningful given the high level of average risk perception (8.3 on a 10-point scale) in the control group.

For the non-at-risk group, we observe positive improvements in both risk comprehension and perception; however, most of the point estimates are statistically insignificant. The only exceptions are the significant improvement in risk comprehension by 8% for the group where we changed the order of information (T2) and the significant improvement in risk perception by 5% for the group where the salience of information was enhanced (T3). Importantly, while the magnitude of treatment effects appears larger for the at-risk group compared to the non-at-risk group, the interaction terms capturing differences between these groups are not statistically significant. Thus, although the direction and size of the coefficients suggest bigger treatment effects for at-risk investors, we cannot statistically confirm differential effects across these groups. Overall, we derive two main findings from Table 8: (a) most of the treatment effect is driven by respondents who are at risk of investing in crypto assets in the future, and (b) both the order of information and increased salience of risk hold potential in improving the understanding of the risk associated with investments in crypto assets for the at-risk investor subgroup.

[10] Figure A5 presents the likelihood of various demographic, financial, and personality groups being classified as at-risk. The analysis reveals that younger individuals, females, those with no prior investment experience, and individuals with low digital product usage are significantly more likely to fall into the at-risk category.

Table 8. Treatment Effect Heterogeneity by At-Risk Investor (Follow Media but Not Invest)

VARIABLES	(1) RC Crypto	(2) RP Stocks	(3) RP Crypto	(4) Rec Stocks	(5) Rec Crypto	(6) WHC Lose	(7) WHC Win	(8) WHS Lose	(9) WHS Win
TE T1 if Not At-Risk	1.510	-0.231	0.131	0.014	0.003	-0.079	-0.127	-0.016	-0.076
	(2.783)	(0.195)	(0.181)	(0.048)	(0.042)	(0.180)	(0.190)	(0.170)	(0.187)
TE T2 if Not At-Risk	5.296*	0.017	0.166	0.064	-0.011	0.173	0.026	0.231	-0.085
	(2.815)	(0.200)	(0.190)	(0.048)	(0.043)	(0.182)	(0.194)	(0.172)	(0.195)
TE T3 if Not At-Risk	4.421	-0.018	0.374**	0.002	-0.037	-0.084	-0.212	-0.024	-0.152
	(2.719)	(0.192)	(0.176)	(0.047)	(0.041)	(0.187)	(0.200)	(0.176)	(0.196)
T1 x At-Risk	3.383	0.086	0.361	0.046	0.018	-0.171	0.164	-0.225	-0.042
	(3.472)	(0.260)	(0.234)	(0.061)	(0.050)	(0.236)	(0.248)	(0.225)	(0.252)
T2 x At-Risk	3.248	-0.020	0.413*	-0.025	0.010	-0.406*	0.026	-0.443*	0.108
	(3.357)	(0.263)	(0.242)	(0.061)	(0.049)	(0.239)	(0.253)	(0.228)	(0.255)
T3 x At-Risk	2.141	-0.277	0.263	0.095	0.031	0.081	-0.140	-0.040	-0.011
	(3.289)	(0.254)	(0.226)	(0.061)	(0.048)	(0.245)	(0.255)	(0.232)	(0.257)
Observations	2,005	2,005	2,005	2,005	2,005	2,005	2,005	2,005	2,005
TE T1 if At-Risk	4.893**	-0.145	0.492***	0.060	0.020	-0.250	0.036	-0.241	-0.118
TE T2 if At-Risk	8.544***	-0.003	0.579***	0.039	-0.001	-0.233	0.052	-0.212	0.023
TE T3 if At-Risk	6.562***	-0.295*	0.638***	0.097**	-0.006	-0.004	-0.352**	-0.065	-0.162
Control Mean if At-Risk	70.35	6.631	8.397	0.343	0.0994	3.571	3.788	4.167	4.343
Control Mean if Not At-Risk	63.42	6.379	7.989	0.463	0.247	3.805	3.874	4.300	4.300

Notes: This table reports OLS estimates of treatment effects. For each outcome variable, we report the coefficients of interest and their robust standard errors in parentheses. TE refers to absolute treatment effects for the stated group. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

8.6 Heterogeneity: Crypto Asset Investors

In Table 9, we explore heterogeneity by ever invested in crypto assets. For the group that has invested in crypto assets, we do not find any statistically significant improvements in any of our primary or secondary outcomes. This is in line with several experiments that have concluded that risk warnings are largely ineffective for those who have already invested in high-risk investments. Ben-Zion et al. (2013) demonstrated that investors who were already engaged in high-risk investments, despite the introduction of risk warnings, continued to allocate a similar proportion of their investments to high-risk funds, indicating that their prior investment decisions and the potential returns overshadowed any new risk information provided. Another experiment by Hüsser (2015) investigated the impact of risk disclosures in mutual fund advertisements on investors with varying levels of financial knowledge. The study found that strongly worded risk warnings had a significant impact on low-knowledge investors but were ineffective for high-knowledge investors who had already committed to high-risk investments. These experienced investors tended to rely on their past performance heuristics and overconfidence, which neutralized the effect of the risk warnings. This indicates that high-risk investors' established beliefs and confidence in their decision-making process can render new risk warnings ineffective.

On the other hand, respondents who have never invested in crypto assets show significant improvements in both risk comprehension and perception across all treatment groups. We find evidence in favor of both order and salience of information. It's not surprising that the findings in Table 8 are similar to those in Table 9. This is because a significant majority of respondents who reported no investments in crypto assets are actually those who follow crypto asset updates on social media. This makes this group potentially vulnerable to aggressive social media campaigns and advertising about crypto assets.

Table 9. Treatment Effect Heterogeneity by Ever Invested in Crypto Assets

VARIABLES	(1) RC Crypto	(2) RP Stocks	(3) RP Crypto	(4) Rec Stocks	(5) Rec Crypto	(6) WHC Lose	(7) WHC Win	(8) WHS Lose	(9) WHS Win
TE T1 if Not Inv Crypto	3.214*	-0.212	0.331***	0.034	0.007	-0.199	-0.035	-0.176	-0.100
	(1.826)	(0.140)	(0.125)	(0.032)	(0.023)	(0.124)	(0.131)	(0.121)	(0.135)
TE T2 if Not Inv Crypto	7.733***	0.052	0.486***	0.060*	-0.015	-0.118	0.017	-0.090	-0.085
	(1.676)	(0.143)	(0.128)	(0.032)	(0.022)	(0.128)	(0.133)	(0.124)	(0.135)
TE T3 if Not Inv Crypto	5.390***	-0.195	0.551***	0.076**	-0.009	-0.023	-0.302**	-0.058	-0.109
	(1.671)	(0.137)	(0.121)	(0.032)	(0.022)	(0.131)	(0.134)	(0.125)	(0.137)
T1 x Inv Crypto	0.104	0.254	0.082	0.028	0.034	0.069	-0.030	0.103	0.003
	(4.823)	(0.362)	(0.324)	(0.088)	(0.086)	(0.346)	(0.356)	(0.314)	(0.354)
T2 x Inv Crypto	-4.472	-0.182	-0.421	-0.097	0.032	0.201	0.125	0.233	0.428
	(4.941)	(0.350)	(0.329)	(0.088)	(0.085)	(0.331)	(0.363)	(0.315)	(0.362)
T3 x Inv Crypto	0.073	0.196	-0.120	-0.125	-0.060	-0.118	0.010	0.065	-0.272
	(4.727)	(0.349)	(0.309)	(0.087)	(0.083)	(0.341)	(0.362)	(0.320)	(0.367)
Observations	2,005	2,005	2,005	2,005	2,005	2,005	2,005	2,005	2,005
TE T1 if Inv Crypto	3.319	0.041	0.413	0.062	0.042	-0.129	-0.065	-0.074	-0.096
TE T2 if Inv Crypto	3.261	-0.129	0.065	-0.037	0.017	0.084	0.142	0.143	0.343
TE T3 if Inv Crypto	5.463	0.001	0.431	-0.049	-0.069	-0.141	-0.292	0.006	-0.382
Control Mean if Inv Crypto	69.76	69.76	69.76	69.76	69.76	69.76	69.76	69.76	69.76
Control Mean if Not Inv Crypto	67.44	67.44	67.44	67.44	67.44	67.44	67.44	67.44	67.44

Notes: This table reports OLS estimates of treatment effects. For each outcome variable, we report the coefficients of interest and their robust standard errors in parentheses. TE refers to absolute treatment effects for the stated group. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

9 Conclusion

This paper builds on the work of (Delias et al., 2022) and provides causal evidence on the impact of behaviorally informed risk warnings, with either past return information, re-ordered information (returns shown before warnings), or risk warnings paired with price volatility cues. We find that behaviorally informed risk warnings combined with crypto asset returns information significantly improve risk comprehension and perception of crypto assets. Moreover, adjusting the order of information (i.e., showing warnings after returns) and increasing the salience of risk information (i.e., combining warnings with volatility information) can further amplify these treatment effects.

Importantly, the effects are concentrated among at-risk investors, i.e., those who follow crypto asset related content on social media but have not yet invested. Findings from a predictive modeling exercise (see Figure A5 in Appendix) indicate that older individuals, those with zero investment experience, females, and individuals with limited digital product usage are significantly more likely to be at-risk. Given that these vulnerable groups are at risk of being targeted by marketing campaigns from some actors in this space, our results underscore the importance of tailored risk warnings that account for behavioral tendencies and the information processing habits of different demographic groups. We do not find any effect among those who have already invested in crypto assets. This may be because their investment decisions are shaped more by realised outcomes rather than ex-ante warnings. Given that only 15% of our sample reported having invested in crypto assets, the remaining 85% are potentially more susceptible to return-heavy promotional content and may benefit the most from such disclosures.

The implications of these findings are multifaceted. For policymakers, the results support their mandate to design and implement risk communication strategies that are not only informative but also behaviorally cognizant. Enhanced risk warnings that strategically increase the salience of critical information and employ recency effects can lead to better-informed investment decisions, thereby safeguarding individuals at risk of investments in crypto assets. In conclusion, our research contributes to the broader discourse on financial literacy and consumer protection by highlighting the critical role of information order and salience in risk communication. Future research could explore the longitudinal effects of such interventions and extend the analysis to other high-risk financial products. As the financial landscape continues to evolve with the advent of novel investment opportunities, the need for effective and behaviorally informed regulatory frameworks becomes increasingly important to help and protect less experienced retail investors to make more informed investment decisions.

References

Aditya, R., Zanesty, R., Arya, T., Prakasa, D., Chantika, I., and Rakhmawati, N. A. (2022). Analisis pengaruh influencer sosial media terhadap keputusan masyarakat indonesia dalam pembelian cryptocurrency. *Majalah Bisnis IPTEK*.

Aiello, D., Baker, S. R., Balyuk, T., Di Maggio, M., Johnson, M. J., and Kotter, J. D. (2023). Who invests in crypto? wealth, financial constraints, and risk attitudes. Working Paper 31856, National Bureau of Economic Research.

Almeida, D., Dionísio, A., Vieira, I., and Ferreira, P. (2022). Uncertainty and risk in the cryptocurrency market. *Journal of Risk and Financial Management*, 15(11):532.

Almeida, J. and Gonçalves, T. C. (2023). A systematic literature review of investor behavior in the cryptocurrency markets. *Journal of Behavioral and Experimental Finance*, 37:100785.

Alvia, L. and Sulistiawan, D. (2010). The examination of recency and knowledge effect in investment decision making: An experimental study. *Indonesian Journal of Accounting Research*, 13(1):45–58.

Aprayuda, R., Misra, F., and Kartika, R. (2021). Does the order of information affect investors' investment decisions? experimental investigation. 22:150–172.

Auer, R. and Tercero-Lucas, D. (2022). Distrust or speculation? the socioeconomic drivers of us cryptocurrency investments. *Journal of Financial Stability*, 62:101066.

Auti, P. D. (2023). Web based platform for startups and investors to connect and predict investment returns using deep learning. *International Journal for Research in Applied Science and Engineering Technology*.

Baker, H. and Filbeck, G. (2015). Investment risk management.

Baker, H. K. and Puttonen, V. (2017). *Investment traps exposed: Navigating investor mistakes and behavioral biases*. Emerald Publishing Limited.

Balu, D. S., Gaikwad, Deshpande, D. M., and Gautam, D. I. (2023). Role of social media information in influencing investment preferences of retail investors: An empirical study. *Journal of Informatics Education and Research*.

Balutel, D., Henry, C., Vásquez, J., and Voia, M. (2022). Bitcoin adoption and beliefs in canada. *Canadian Journal of Economics/Revue canadienne d'économique*, 55(4):1729–1761.

Bannier, C., Meyll, T., Röder, F., and Walter, A. (2019). The gender gap in 'bitcoin literacy'. *Journal of Behavioral and Experimental Finance*, 22:129–134.

Barber, B., Odean, T., and Zheng, L. (2005). Out of sight, out of mind: The effects of expenses on mutual fund flows. *The Journal of Business*, 78(6):2095–2120.

Barker, J. (2025). Best stablecoin interest rates & yields in 2025. https://www.datawallet.com/crypto/best-stablecoin-interest-rates. Datawallet Research; accessed 22 July 2025.

Ben-Zion, U., Krupalnik, L., and Shavit, T. (2013). The effect of a high-risk stock fund on long-term investment: An experimental study. *Journal of Behavioral Finance*, 14:53 – 64.

Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of consumer psychology*, 24(4):586–607.

Berliana, B., Ambarwati, S. D. A., and Yacobus, A. (2022). Determinants of capital market investment interest in the millenial generation in the covid-19 pandemic. *International Journal of Economics, Business and Accounting Research (IJEBAR)*.

Bertrand, M. and Morse, A. (2011). Information disclosure, cognitive biases, and payday borrowing. *Journal of Finance*, 66(6):1865–1893.

Beshears, J., Choi, J. J., Laibson, D., and Madrian, B. C. (2009). How does simplified disclosure affect individuals' mutual fund choices? Working Paper 14859, National Bureau of Economic Research.

BIS (2021). Annual economic report.

Bollinger, B., Leslie, P., and Sorensen, A. (2011). Calorie posting in chain restaurants. *American Economic Journal: Economic Policy*, 3(1):91–128.

Campino, J. and Yang, S. (2024). Decoding the cryptocurrency user: An analysis of demographics and sentiments. *Heliyon*, 10(5):e26671.

Capital One Shopping Research Team (2024). Retailers that accept cryptocurrency: 2024 statistics. https://capitaloneshopping.com/research/retailers-that-accept-cryptocurrency/. Accessed 22 July 2025.

Carbó-Valverde, S., Cuadros-Solas, P. J., and Rodríguez-Fernández, F. (2025). Cryptocurrency ownership and cognitive biases in perceived financial literacy. *Journal of Behavioral and Experimental Finance*, 45:101019.

CBI (2022). Consumer warning on virtual currencies.

CBI (2024a). Crypto - consumer information.

CBI (2024b). Markets in crypto-assets regulation (micar).

CCPC (2021). Ccpc investments research. *Investment Research*.

CMC (2025). Coinmarketcap.

Daigle, R. J., Pinsker, R., and Pitre, T. J. (2015). The impact of order effects on nonprofessional investors' belief revision when presented a long series of disclosures in an experimental market setting. *Accounting Horizons*, 29:313–326.

Delias, D., Farghly, F., Hayes, L., Ng, C., and Spohn, M. (2022). Going beyond 'capital at risk': Behaviourally informed risk warnings for high-risk investment products. *Financial Conduct Authority, Research Notes*.

Desanctis, G. and Jarvenpaa, S. L. (1989). Graphical representation of accounting data for financial forecasting: An experimental investigation. *Accounting, Organizations and Society*, 14(5-6):509–525.

Durkin, T. A. and Elliehausen, G. E. (2011). *Truth in lending: Theory, history, and a way forward*. Oxford University Press, USA.

Döbrich, C., Wollersheim, J., Spörrle, M., and Welpe, I. M. (2014). Letting go of your losses: Experimental evidence for debiasing the disposition effect in private investment decisions. *Journal of Management and Strategy*.

Elad, B. (2024). Cryptocurrency-based remittance statistics 2025: Adoption, costs, and innovations. https://coinlaw.io/cryptocurrency-based-remittance-statistics/. Updated 19 December 2024; accessed 22 July 2025.

ESMA (2022). Eu financial regulators warn consumers on the risks of crypto-assets.

ESMA (2024a). Crypto-assets on the rise but reamining very risky.

ESMA (2024b). Requirements when posting investments recommendations on social media.

EU (2023). Markets in crypto-assets regulation (micar).

Fiqri, F. F. and Oetarjo, M. (2023). The influence of social media, brand image and price on purchase decisions on crypto asset exchange platform applications. *Academia Open*.

Fujiki, H. (2020). Who adopts crypto assets in japan? evidence from the 2019 financial literacy survey. *Journal of the Japanese and International Economies*, 58:101107.

Gui, Z., Huang, Y., and Zhao, X. (2020). Whom to educate? financial literacy and investor awareness. *Financial Literacy eJournal*.

Hartono, J. (2004). How, why and when investors revise their beliefs to company information and their implications to firms announcement policy. *ANDI Yogyakarta*.

Hasso, T., Pelster, M., and Breitmayer, B. (2019). Who trades cryptocurrencies, how do they trade it, and how do they perform? evidence from brokerage accounts. *Journal of Behavioral and Experimental Finance*, 23:64–74.

Hastings, J. S. and Weinstein, J. M. (2008). Information, school choice, and academic achievement: Evidence from two experiments. *Quarterly Journal of Economics*, 123(4):1373–1414.

Hellmann, A., Yeow, C., and Mello, L. D. (2017). The influence of textual presentation order and graphical presentation on the judgements of non-professional investors. *Accounting and Business Research*, 47:455 – 470.

Hogarth, R. M. and Einhorn, H. J. (1992). Order effects in belief updating: The belief-adjustment model. *Cognitive psychology*, 24(1):1–55.

Huber, J., Palan, S., and Zeisberger, S. (2019). Does investor risk perception drive asset prices in markets? experimental evidence. *Journal of Banking Finance*.

Hüsser, A. (2015). The role of investors' objective financial knowledge on the assessment of risk disclosures in mutual fund advertisements. *Journal of Financial Services Marketing*, 20:5–22.

Hwang, S. and Satchell, S. E. (2010). How loss averse are investors in financial markets? *Journal of Banking & Finance*, 34(10):2425–2438.

Jagolinzer, A. (2024). How crypto influencers manipulate vulnerable investors. *Cambridge Judge Business School Insights*. Accessed: 2025-07-21.

Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics*, 125.

Jin, G. Z. and Leslie, P. (2003). The effect of information on product quality: Evidence from restaurant hygiene grade cards. *Quarterly Journal of Economics*, 118(2):409–451.

Kadous, K., Mercer, M., and Zhou, Y. (2024). Why do investors rely on low-quality investment advice? experimental evidence from social media platforms. *SSRN*. https://ssrn.com/abstract=2968407 or http://dx.doi.org/10.2139/ssrn.2968407.

Kahneman, D. (2013). Thinking, fast and slow (herdruk). *Farrar, Straus and Giroux*.

Kahneman, D. and Tversky, A. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157):1124–1131.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291.

Kawai, D., Cuevas, A., Routledge, B. R., Soska, K., Zetlin-Jones, A., and Christin, N. (2023). Is your digital neighbor a reliable investment advisor? *Proceedings of the ACM Web Conference 2023*.

Khang, I. (2012). On the role of subjective valuation in housing investment.

Krause, D. (2025). The genius act: A new era of us stablecoin regulation. *Available at SSRN 5127407*.

Kroszner, R. S. (2007). Creating more effective consumer disclosures. Speech, George Washington University School of Business, Financial Services Research Program Policy Forum, Washington, DC.

Lacko, J. M. and Pappalardo, J. K. (2007). Improving consumer mortgage disclosures: An empirical assessment of current and prototype disclosure forms. Technical report, Federal Trade Commission Bureau of Economics, Washington, DC.

Lee, J. G. (2022). A study on the changes in the asset portfolio before and after covid-19. *The Korean Data Analysis Society*.

Linciano, N., Lucarelli, C., Gentile, M., and Soccorso, P. (2018). How financial information disclosure affects risk perception. evidence from italian investors' behaviour. *The European Journal of Finance*.

Lisauskiene, N., Darskuviene, V., and Butkus, M. (2023). Are robo-advisors reducing the disposition effect? the moderating role of gender and financial literacy. *The Moderating Role of Gender and Financial Literacy*.

Loewenstein, G., O'Donoghue, T., and Rabin, M. (2003). Projection bias in predicting future utility. *the Quarterly Journal of economics*, pages 1209–1248.

Ludwig, Z. and Perkowski, P. (2021). An analysis of how twitter impacts financial markets. *Journal of Student Research*.

Mai, F., Bai, Q., Shan, J., Wang, X., and Chiang, R. (2016). The impacts of social media on bitcoin performance.

Merkley, K. J., Pacelli, J., Piorkowski, M., and Williams, B. (2024). Crypto-influencers. *Review of Accounting Studies, Forthcoming*.

Mirtaheri, M., Abu-El-Haija, S., Morstatter, F., Steeg, G. V., and Galstyan, A. (2021). Identifying and analyzing cryptocurrency manipulations in social media. *IEEE Transactions on Computational Social Systems*.

Mittal, A., Dhiman, V., Singh, A., and Prakash, C. (2019). Short-term bitcoin price fluctuation prediction using social media and web search data. *2019 Twelfth International Conference on Contemporary Computing (IC3)*, pages 1–6.

Mulligan, E. J. and Hastie, R. (2005). Explanations determine the impact of information on financial investment judgments. *Journal of Behavioral Decision Making*, 18:145–156.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Newall, P. and Weiss-Cohen, L. (2022). The gamblification of investing: How a new generation of investors is being born to lose. *International Journal of Environmental Research and Public Health*, 19.

Panos, G. A., Karkkainen, T., and Atkinson, A. (2020). Financial literacy and attitudes to cryptocurrencies.

Pelster, M., Breitmayer, B., and Hasso, T. (2019). Are cryptocurrency traders pioneers or just risk-seekers? evidence from brokerage accounts. *Mutual Funds*.

Romano, J. P., Shaikh, A. M., and Wolf, M. (2010). Hypothesis testing in econometrics. *Annu. Rev. Econ.*, 2(1):75–104.

Seira, E., Elizondo, A., and Laguna-Müggenburg, E. (2017). Are information disclosures effective? evidence from the credit card market. *American Economic Journal: Economic Policy*, 9(1):277–307.

Senz, K. (2023). When celebrity ‘crypto-influencers’ rake in cash, investors lose big. *Harvard Business School Working Knowledge*. Accessed: 2025-07-21.

Shavit, T., Lahav, E., and Rosenboim, M. (2016). Don’t fear risk, learn about it: how familiarity reduces perceived risk. *Applied Economics Letters*, 23:1069 – 1072.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance*, 40(3):777–790.

Statista, G. C. S. (2023). Statista global consumer survey 2023.

Steinert, L. and Herff, C. (2018). Predicting altcoin returns using social media. *PLoS ONE*, 13.

Steinmetz, F., Meduna, M., Ante, L., and Fiedler, I. (2021). Ownership, uses and perceptions of cryptocurrency: Results from a population survey. *Technological Forecasting and Social Change*, 173:121073.

Tseng, S. (2013). Information searches affect individual investment preferences: Testing a moderating effect of income. *International journal of social science and humanity*, pages 133–138.

Tversky, A. and Fox, C. (1995). Weighing risk and uncertainty. *Psychological Review*, 102:269–283.

Tversky, A. and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, 211(4481):453–458.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4):297–323.

Vlaev, I., Chater, N., and Stewart, N. (2009). Dimensionality of risk perception: Factors affecting consumer understanding and evaluation of financial risk. *Journal of Behavioral Finance*, 10(3):158–181.

Wang, M., Keller, C., and Siegrist, M. (2011). The less you know, the more you are afraid of–a survey on risk perceptions of investment products. *Journal of Behavioral Finance*, 12(1):9–19.

Weathers, D., Swain, S. D., and Carlson, J. P. (2012). Why consumers respond differently to absolute versus percentage descriptions of quantities. *Marketing Letters*, 23(4):943–957.

Weber, E. U., Siebenmorgen, N., and Weber, M. (2005). Communicating asset risk: How name recognition and the format of historic volatility information affect risk perception and investment decisions. *Risk Analysis*, 25(3):597–609.

Weber, M., Candia, B., Coibion, O., and Gorodnichenko, Y. (2023). Do you even crypto, bro? cryptocurrencies in household finance. Working Paper 31284, National Bureau of Economic Research.

Wilcox, R. T. (2003). Bargain hunting or star gazing? investors' preferences for stock mutual funds. *Journal of Business*, 76(4):645–663.

Williams, J. L. (2005). Remarks by julie l. williams acting comptroller of the currency before women in housing and finance and the exchequer club. Speech, Washington, DC.

Woodward, S. E. and Hall, R. E. (2012). Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence. *American Economic Review*, 102(7):3249–3276.

Yamamoto, H., Sakaji, H., Matsushima, H., Yamashita, Y., Osawa, K., Izumi, K., and Shimada, T. (2019). Forecasting crypto-asset price using influencer tweets. pages 940–951.

Yao, R. and Curl, A. (2011). Do market returns influence risk tolerance? evidence from panel data. *Journal of Family and Economic Issues*, 32:532–544.

Zheng, W., Li, B., Huang, Z., and Chen, L. (2021). Why was there more household stock market participation during the covid-19 pandemic? *Finance Research Letters*, 46:102481 – 102481.

Zhu, P., Zhang, X., Wu, Y., Zheng, H., and Zhang, Y. (2021). Investor attention and cryptocurrency: Evidence from the bitcoin market. *PLoS ONE*, 16.

Appendix

The appendix contains supplementary figures and tables referenced in the main text. Figures A1 to A4 illustrate the investment browsing experience for each study arm, including the control and the three treatment groups. Table A provides details on how the primary and secondary outcomes were constructed. Tables B1 and B2 report Intention-to-Treat (ITT) estimates for primary and secondary outcomes, respectively, and include coefficients for all control variables used in the regression models. Finally, Figure A5 presents the results from a logit model estimating the probability of belonging to the at-risk investor group.

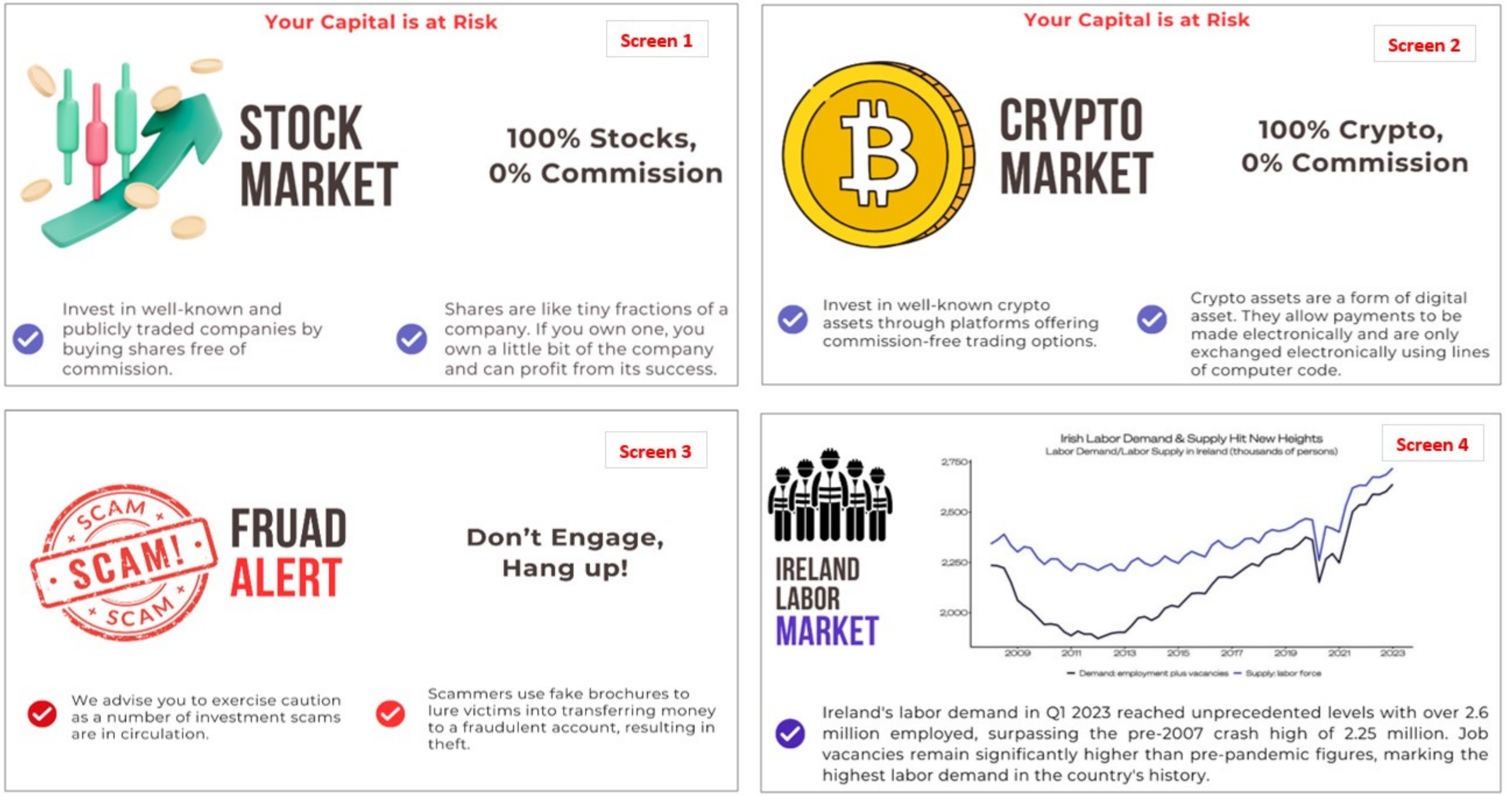


Figure A1. Investment Browsing Experience: Control Group

Notes: This figure shows the investment browsing experience for participants assigned to the control group. All participants were shown a sequence of four screens designed to simulate a real-world investment promotion environment. Screen 1 presented promotional content for the stock market, paired with a standard risk warning. Screen 2 displayed similar promotional content for crypto assets, also including a standard risk warning. Screen 3 provided a neutral informational message on investment scams, and Screen 4 offered labor market statistics in Ireland. Unlike the treatment groups, the control group received no behaviourally informed risk warnings or targeted return/volatility cues.

Figure A2. Investment Browsing Experience: T1 (Warnings + Returns)

Notes: This figure shows the investment browsing experience for participants assigned to Treatment 1 (Warnings + Returns). All participants were first shown promotional content for stocks on Screen 1, followed by a standard risk warning. Screen 2 presented a standard promotion for crypto assets, while Screen 3 introduced a behaviourally informed risk warning designed to heighten perceived risk. Screens 4 and 5 then displayed positively framed return information, including a historical return narrative and a stylized price chart demonstrating the growth in Bitcoin's value.

Figure A3. Investment Browsing Experience: T2 (Returns + Warnings)

Notes: This figure shows the investment browsing experience for participants in Treatment 2 (Returns + Warnings). As in Treatment 1, participants viewed stock and crypto asset promotions, and were exposed to both behaviourally informed warnings and return information for crypto assets. However, the order of information is reversed: positively framed return content appears before the warning message.

Figure A4. Investment Browsing Experience: T3 (Warnings + Volatility)

Notes: This figure shows the investment browsing experience for participants in Treatment 3 (Warnings + Volatility). Participants viewed stock and crypto asset promotions, with a standard risk warning shown for stocks. For crypto assets, a behaviourally informed warning was followed by price volatility cues highlighting the potential for extreme fluctuations in crypto assets. This treatment increased risk salience by pairing the warning with information about crypto asset market volatility, rather than return-focused content.

Table A1. Construction of Primary & Secondary Outcomes

No	Outcome Name	Scale	Question
1	Risk Comprehension	Percentage	1. Which of these best describes the risk associated with crypto assets? - You are unlikely to lose any money you invested - You may lose some of the money you invested - You may lose all of the money you invested - You may lose all of the money you invested, and then still owe more on top of that 2. What will happen to your money if the value of your crypto asset investment falls close to €0? - I will likely be able to apply for compensation schemes - The crypto trading platform will return my investment if it is regulated by ECB or CBI - I am unlikely to get my money back - I will be able to sell my crypto asset as soon as its value declines to minimise my losses 3. If you are considering investing in crypto assets, which approach reflects a cautious and informed perspective, given the speculative and high-risk nature of these investments? - Invest a large proportion of your investable capital into multiple crypto assets to spread your risk - Invest a large proportion of your investable capital into a single crypto asset to maximise potential gains - Only invest if you are new to investing, there are more stable and profitable investments out there for experienced investors - Invest a relatively small portion of your investable capital in crypto assets, and the majority in lower risk investment 4. What are the key risks associated with investing in crypto assets? - Loss of capital and illiquidity - Loss of capital and volatility of prices - Loss of capital, illiquidity, and volatility of prices - Investing in crypto assets is relatively low risk
2	Risk Perception (Stocks)	1 to 10	On a scale of 1 to 10, with 1 being not risky at all and 10 being the riskiest, how do you perceive the risk associated with investing in stocks?
3	Risk Perception (Crypto Assets)	1 to 10	On a scale of 1 to 10, with 1 being not risky at all and 10 being the riskiest, how do you perceive the risk associated with investing in crypto assets?
4	Stocks Recommendation	Binary (1/0)	Suppose you were to give financial advice to a hypothetical friend who is planning to buy a house in the next couple of years. Your friend saved €16,000 towards the €20,000 deposit and now wants to boost their savings by investing. Would you recommend that your friend invests in stocks?
5	Crypto Asset Recommendation	Binary (1/0)	Suppose you were to give financial advice to a hypothetical friend who is planning to buy a house in the next couple of years. Your friend saved €16,000 towards the €20,000 deposit and now wants to boost their savings by investing. Would you recommend that your friend invests in crypto assets?
6	Willingness to Sell or Hold Stocks	1 to 7	Suppose, one year ago, you invested €3,400 of your savings in stocks. At the time you bought stocks of two companies: Company X (for €2,200) and Company Y (for €1,200). - Company X stocks have dropped by 23% from €2,200 to €1,700 (losing) - Company Y stocks have risen by 50% from €1,200 to €1,800 (winning) 1. How likely will you sell or hold Company X stocks? 2. How likely will you sell or hold Company Y stocks?
7	Willingness to Sell or Hold Crypto Assets	1 to 7	Suppose, one year ago, you invested €3,400 of your savings in cryptoassets. At the time you bought two cryptoassets: Crypto Asset A (for €2,200) and Crypto Asset B (for €1,200). - Crypto Asset A has dropped by 23% from €2,200 to €1,700 (losing) - Crypto Asset B has risen by 50% from €1,200 to €1,800 (winning) 1. How likely will you sell or hold Company X stocks? 2. How likely will you sell or hold Company Y stocks?

Table A2. Treatment Effect on Primary Outcomes

VARIABLES	(1) RC Crypto (%)	(2) RP Stocks (1-10)	(3) RP Crypto (1-10)	(4) Rec Stocks (1/0)	(5) Rec Crypto (1/0)
T1: Warnings + Returns	3.121*	-0.171	0.327***	0.033	0.008
	(1.766)	(0.130)	(0.120)	(0.030)	(0.022)
T2: Returns + Warnings	7.889***	-0.007	0.458***	0.052*	-0.011
	(1.662)	(0.132)	(0.119)	(0.031)	(0.022)
T3: Warnings + Volatility	6.357***	-0.185	0.571***	0.060**	-0.022
	(1.646)	(0.127)	(0.115)	(0.031)	(0.022)
Age	2.268***	0.022	0.251***	-0.018*	-0.028***
	(0.543)	(0.042)	(0.040)	(0.010)	(0.007)
Dublin	2.140	-0.251**	-0.069	0.018	-0.008
	(1.406)	(0.106)	(0.098)	(0.025)	(0.018)
Male	1.904	-0.045	0.135	0.017	-0.001
	(1.288)	(0.099)	(0.090)	(0.023)	(0.017)
Income > €49,000	3.825***	-0.173*	0.136	0.036	-0.010
	(1.280)	(0.100)	(0.089)	(0.024)	(0.017)
Digital Products Use (%)	0.088**	0.002	0.009***	0.003***	0.000
	(0.045)	(0.003)	(0.003)	(0.001)	(0.001)
Follow Crypto Updates	10.874***	0.100	0.571***	-0.038	-0.079***
	(1.411)	(0.102)	(0.098)	(0.024)	(0.018)
Ever Invested in Crypto Assets	3.164*	-0.374***	-0.195	0.135***	0.230***
	(1.901)	(0.136)	(0.128)	(0.034)	(0.030)
Observations	2,005	2,005	2,005	2,005	2,005

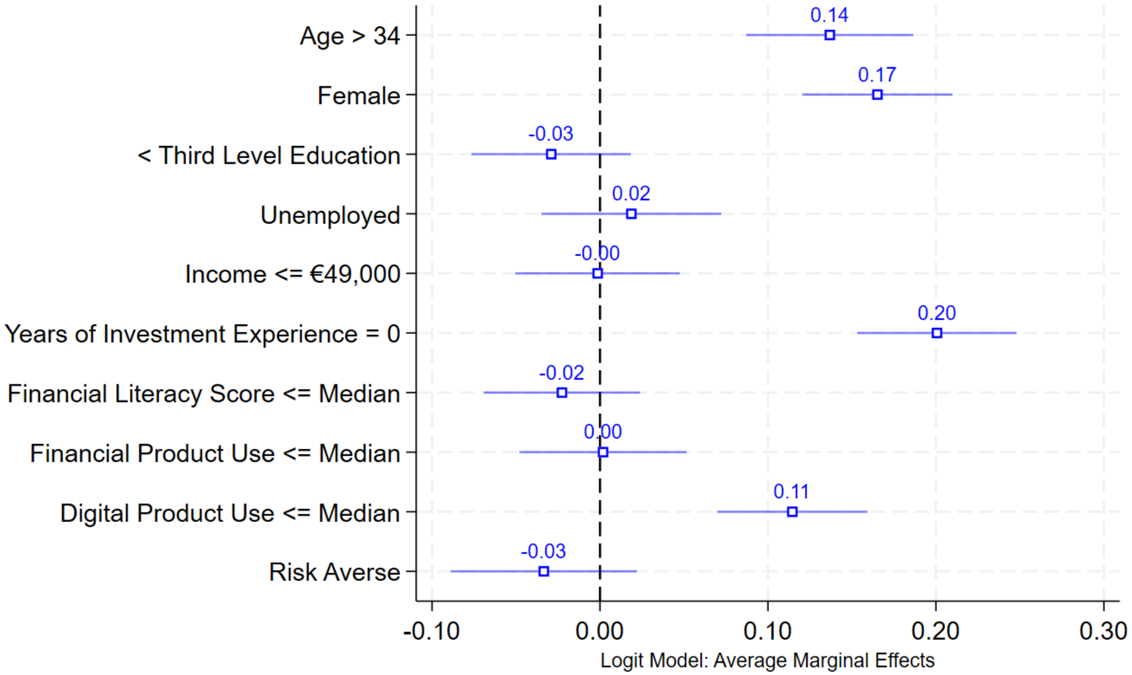
Notes: This table reports OLS estimates of treatment effects. Controls include age, region, gender, a binary variable for income above €49,000, a digital product use score, a dummy variable indicating whether the respondent follows crypto market updates on social media, and a dummy variable indicating whether the respondent has ever invested in crypto assets. Columns 1-5 show results for our primary outcomes; risk comprehension expressed in percentage terms, risk perception for stocks and crypto assets expressed as ordinal variables with higher values meaning more risk perception and finally two binary variables which take the value of 1 if the respondent would like to recommend stocks or crypto assets to a hypothetical friend and zero otherwise. For each outcome variable, we report the coefficients of interest and their robust standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

Table A3. Treatment Effect on Secondary Outcomes

VARIABLES	(1) WHS Losing	(2) WHS Losing	(3) WHS Losing	(4) WHS Losing
T1: Warnings + Returns	-0.168	-0.168	-0.168	-0.168
	(0.113)	(0.113)	(0.113)	(0.113)
T2: Returns + Warnings	-0.034	-0.034	-0.034	-0.034
	(0.115)	(0.115)	(0.115)	(0.115)
T3: Warnings + Volatility	-0.039	-0.039	-0.039	-0.039
	(0.116)	(0.116)	(0.116)	(0.116)
Age	0.052	0.052	0.052	0.052
	(0.037)	(0.037)	(0.037)	(0.037)
Dublin	0.045	0.045	0.045	0.045
	(0.095)	(0.095)	(0.095)	(0.095)
Male	-0.016	-0.016	-0.016	-0.016
	(0.087)	(0.087)	(0.087)	(0.087)
Income > €49,000	0.330***	0.330***	0.330***	0.330***
	(0.092)	(0.092)	(0.092)	(0.092)
Digital Products Use (%)	0.007***	0.007***	0.007***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)
Follow Crypto Updates	-0.071	-0.071	-0.071	-0.071
	(0.089)	(0.089)	(0.089)	(0.089)
Ever Invested in Crypto Assets	0.529***	0.529***	0.529***	0.529***
	(0.124)	(0.124)	(0.124)	(0.124)
Observations	2,005	2,005	2,005	2,005

Notes: This table reports OLS estimates of treatment effects. Controls include age, region, gender, a binary variable for income above €49,000, a digital product use score, a dummy variable indicating whether the respondent follows crypto market updates on social media, and a dummy variable indicating whether the respondent has ever invested in crypto assets. Columns 1-4 show results for our secondary outcomes. WHS and WHC stand for willingness to hold or sell a stock or crypto asset on a scale of 1-7, where higher values mean more willingness to hold and lower values mean more willingness to sell. We report WHS and WHC for both losing and winning stocks and crypto assets. For each outcome variable, we report the coefficients of interest and their robust standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels.

Figure A5. Predictors of At-Risk Investors, N=2005



Notes: The figure above reports marginal effect estimates from a logit model that regress At-Risk (1/0) on a battery of demographic, financial and personality variables. The variable At-Risk takes the value of 1 if the respondent follows crypto asset updates on media or has considered investing in crypto assets in the past but hasn't ever invested in crypto assets and zero otherwise. The zero category includes respondents who have invested in crypto assets before or haven't considered investing in crypto assets or don't follow crypto updates on media. All variables used in the logit model are binary and point estimates are expressed in percentage points; for example, participants who are $>$ 34 years of age, are 14 percentage points more likely to be in the at-risk investor group relative to those who are $\leq$ 34 years of age, after controlling for all other variables in the model.

T: +353 (0)1 224 6000
www.centralbank.ie
publications@centralbank.ie

Bosca PO 559, Baile Átha Cliath 1, Éire
PO Box 559, Dublin 1, Ireland