The Impact of Experience, Overconfidence and Optimism on Future Cryptocurrency Ownership

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Abstract
Using recent survey data from Sweden, Denmark, and Finland, we analyze the effect of experience with cryptocurrencies, overconfidence and economic expectations on future cryptocurrency ownership. We document that negative experiences with cryptocurrencies and overconfidence positively affect the odds of having cryptocurrency in the future. The results show that owners of ESG products are the most optimistic, with the highest optimism score. This is followed closely by owners of Crypto assets / NFTs and Antiques / Art.

Keywords: cryptocurrency, investment, experience, overconfidence

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1. Introduction

The behavior of individual investors in financial markets is fundamental for understanding market efficiency and has been studied since the inception of the efficient markets hypothesis. Three main concepts underpin this hypothesis: rational decision-making, the absence of consistent irrational behavior, and limits to arbitrage (Shleifer 2000). Beyond market efficiency, individual investor behavior plays a pivotal role in household finance, influencing the distribution of wealth within the economy. Campbell (2006) underscores the importance of understanding these behaviors and their broader implications.

Rapidly growing interest in highly risky and volatile cryptocurrency markets has spurred academic inquiry into factors influencing crypto investments, ranging from socio-demographic factors such as age, gender and education (Hasso et al., 2019; Ante et al., 2022) to cognitive biases (Sudzina et al., 2021). While the role of cognitive biases in investing is well-documented in the context of traditional markets (Baker et al., 2004), that for cryptocurrency markets remains nascent (Yang, 2019; Al Mansour, 2020).

As observed in equity markets, overconfidence, often stemming from past successes, can lead investors to make riskier decisions, believing in their ability to outperform the market consistently. In the volatile realm of cryptocurrencies, where market dynamics are still being understood, such overconfidence, combined with prior investment experience, and young age of an average individual crypto investor, can have amplified effects. Investors might either leverage their experience to navigate this new landscape effectively or, conversely, make misjudgments based on overconfidence, leading to potential pitfalls.

Learning theory indicates that experiences shape expectations and behavior (Malmendier and Nagel, 2011; Kelley and Tetlock 2013), suggesting that variations in behavior and performance may be attributed to learning processes. Other studies, like those by Feng and Seasholes (2005) and Linnainmaa (2010), indicate that investors often adjust strategies based on outcomes, suggesting an element of experimentation in their approach. A growing body of research is dedicated to
understanding how individual investors learn from their experiences. Kelley and Tetlock (2013)
suggest that variations in behavior and performance may be attributed to learning processes. Other
studies, like those by Feng and Seasholes (2005) and Linnainmaa (2010), indicate that investors
often adjust strategies based on outcomes, suggesting an element of experimentation in their
approach. The role of past investment experiences in shaping future crypto investing behaviour
has been understudied in literature, a gap we aim to address.

Overconfidence affects both investor behaviour (Spyrou, 2013) and investment decisions
(Hoffman et al., 2013). It is surprising to note that despite the link between youth and
overconfidence (Prims and Moore, 2017), there are barely any studies that study overconfidence in
the cryptocurrency market, which is dominated by youth, in the 18-34 age bracket¹.

In terms of economic expectations and optimism, studies how clear psychological evidence
that individuals who are optimistic about the future prospects, expect that good outcomes are more
likely to happen than in actuality (Puri and Robinson, 2007, Shepperd et al., 2013). Optimism is a
significant element of utility (Brunnermeier and Parker, 2005). It can cause both overreactions and
underreactions in stock returns (Barberis, Shleifer, and Vishny, 1998). Optimism also plays a crucial
role in financial intermediation (Coval and Thakor, 2005). In situations with short-sale restrictions,
optimism can drive up security prices (Chen, Hong, and Stein, 2003).

To explore the impact of experience, overconfidence and optimism on the prospect of
future cryptocurrency ownership, we analyze unique survey data from three Nordic countries -
Sweden, Denmark, and Finland between 8/11/2022 and 7/12/2022 using multinominal survey-
weighted generalised linear models with inverse-probability weighting and design-based standard
errors. Nordic countries are known for their high rates of digital and technological advancement
and have been slowly, but steadily opening up to cryptocurrencies. The number of cryptocurrency
users in Sweden (and Denmark) jumped from 4% (8%) in 2019 to 9% (11%) in 2021.² As the

¹ Source: authors’ survey results, Finder’s Cryptocurrency Adoption Index.
² Source: https://nordicfintechmagazine.com/crypto-is-taking-a-foothold-in-the-nordics/
methodological framework, we mainly focus on multinomial survey-weighted generalised linear models with inverse-probability weighting and design-based standard errors, using it as the tool to prove our hypothesis based on the observations.

Our research makes several contributions to literature. First, we contribute to the literature on the role of cognitive biases on investor behaviour in cryptocurrency markets, specifically on how personal experiences shape risk-taking behaviour, particularly for highly risky cryptocurrencies. Our findings that negative past experience with cryptocurrencies positively affects the odds of future cryptocurrency ownership is not only counter-intuitive but also in sharp contrast with the findings of Malmendier and Nagel (2011). The fact that individual crypto investors with negative experiences with cryptocurrencies continue to show interest in the asset class could reflect some form of self-serving bias (Miller and Ross, 1975; Campbell and Sedikides, 1999), with these investors likely attributing their losses to factors beyond their control (like market volatility) rather than poor decision-making on their part. This may end up preserving their confidence in the highly volatile asset class even in the future. This highlights an important difference in investor dynamics between traditional and the not-so-well-understood cryptocurrency markets, dominated by the youth.

While this may sound counter-intuitive, contradict those of and might highlight an important contrast between traditional and cryptocurrency market participants, highlighting higher risk-taking or even ‘loss-chasing’ following past investment losses. Second, the data strongly suggests the presence of overconfidence bias (Barber and Odean, 2001).

Second, we document that overconfidence has a positive effect on the odds of having cryptocurrencies in the future. This is in line with Guiso and Jappelli (2006), who document that overconfident investors might overestimate the quality of their own information and underestimate investment risk. Additionally, we show that overconfident individuals show a very high interest in holding cryptocurrencies, irrespective of their past experience with these assets – gains, losses or even no experience. This seems to suggest that overconfidence overrides experience in the context
of cryptocurrency markets, which highlights an important difference in the dynamics of overconfidence compared to traditional markets.

Third, we document that strong overconfidence is associated with a markedly higher trading frequency as witnessed by trading multiple times a day. This could be a result of overestimating one's knowledge and skills, or higher optimism in outperforming the market, leading to higher trading activity. These findings that we document in the context of cryptocurrency markets is in line with behavioral finance literature, where overconfidence has been associated with increased trading activity in the context of traditional financial markets (Barber and Odean, 2000).

Fourth, we show that owners of ESG products are the most optimistic, with the highest optimism score. This is followed closely by owners of Crypto assets / NFTs and Antiques / Art. Females are more optimistic.

Finally, our findings shed light on the gender-age-overconfidence-relationship in the youth-dominated cryptocurrency markets.

2. Theoretical framework

Initial studies (from the 1970s to the 1990s)³ relied on limited data from retail or discount brokerages. Findings from these studies highlighted tendencies like the disposition effect and excessive trading, which were further influenced by factors like gender, marital status, and access to online trading (e.g., Odean 1998, 1999; Barber and Odean 2001, 2002 etc). Later research explores the trading strategies of individual investors and how various behavioral biases affected their choices.

2.1. Experience

There's a growing body of research focusing on how individual investors learn from their experiences. Some findings suggest that investors experiment with their trading strategies and

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adjust based on outcomes. Other studies have documented how households react to their past investment experiences, leading to specific patterns like style-chasing behavior.

Investors use past investment experience in ascertaining the uncertainty of current investments (Nofsinger, 2011). While investors are likely more risk-taking following past investment gains, they are likely to act risk-averse following past financial losses (Nofsinger, 2005). In fact, bad past financial performance has been linked to herding behaviour (Merli & Roger, 2013). Prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) suggests that while "endowment effect" causes individuals to hold riskier assets with past gains, loss aversion leads them to sell assets with past losses.

2.2. Overconfidence

Overconfidence, an important bias in decision-making (Plous, 1993), occurs when investors overstate their skill and knowledge. Overconfidence has been linked to excessive risk-taking (Barbar & Odean, 2000) and under-diversification (Shin et al., 2020). Factors affecting overconfidence include age, investment performance, knowledge, and economic expectations, etc. Using overconfidence as the divergence between objective and subjective financial literacy, Kim et al. (2022) document a positive relationship between overconfidence and crypto investing for US investors.

2.3. Economic expectations

Consumers form expectations based on comprehensible evaluations of the relevant news (Claus & Nguyen, 2018). In turn, expectations might implicitly or explicitly suggest savings, investment, or other financial asset allocations and risk-taking (Beverly et al. 2008; Ampudia & Ehrmann 2017).
Thus, it raises the question of how expectations about future economic conditions affect the odds of having financial assets, especially high-risk crypto assets by youth in Scandinavian countries, such as Denmark, Finland, and Sweden.

Regarding economic forecasts and optimism, research indicates strong psychological evidence that individuals who are hopeful about future outcomes tend to overestimate the likelihood of positive results (Puri and Robinson, 2007; Shepperd et al., 2013). Optimism greatly contributes to perceived utility (Brunnermeier and Parker, 2005). It can lead to exaggerated or muted reactions in stock market returns (Barberis, Shleifer, and Vishny, 1998). Furthermore, optimism holds significant importance in financial intermediation (Coval and Thakor, 2005). When there are limitations on short sales, an optimistic viewpoint can elevate security prices (Chen, Hong, and Stein, 2003).

3. Data and model

3.1. Data

3.1.1. Survey organization

The survey spanning 8/11/2022 - 7/12/2022, comprises 500 respondents in Denmark, 518 in Finland, and 501 in Sweden. The general demographic structures are presented in Figs 1a-1b.

![Age Distribution of Respondents](image1)

Fig. 1a The distribution of the respondents’ age groups

![Distribution of ages, per country](image2)

Fig. 1b. Distribution of ages, per country
After this period, GWI, the agency that managed the survey, assigned a "weight" to each participant, considering factors like age, gender, and educational background. This data was sourced from a mix of data, including census data, to ensure it accurately reflects each market. This approach allows us to gauge the real-world representation of the responses. The weight each participant receives varies by market, influenced by the country's population size and the feasibility of conducting research there.

Given the relatively modest sample sizes in our custom studies, about 500 per country with a total of 1519, the finite population corrections (FPC) are close to 1. For clarity, Denmark stands at 0.9999313, Sweden at 0.9999593, and Finland at 0.9999218. Delving into the randomness of the sample, every custom study is purely random. Moreover, we adjust all our studies to match the population, ensuring the project's data genuinely reflects the online populace.

Managing sampling and non-sampling errors involves several steps. First, population specification error. Since our primary aim is to understand the general population's perspective on crypto assets, with a special focus on the youth, we target a broad audience. The survey has built-in logic that directs specific questions based on prior answers. For instance, someone without a crypto wallet won't be asked about their crypto holdings.

Next, the sample frame error. The agency highlighted that their panels have vast respondent communities, balanced to represent the general population aged 16 and above. Being an online survey, it represents the online demographic. With the 100% internet penetration in our target markets (cryptos), this representation is considered to be accurate.

Selection errors are also addressed. We don't employ river sampling. Participants receive exclusive invites for the study, with the topic unveiled only during the screening phase. As for sampling errors, the agency partners with seasoned panel providers to ensure high quality of the collected data. These providers monitor their panel communities closely. Our potential respondent pool is vast, much larger than our study sample, offering a broad selection base. All eligible participants are invited.
Lastly, ensuring the quality of the sample is essential. Participants who aren't attentive, provide inconsistent answers, or complete the survey at an unusual pace are filtered out.

Bias management is a multi-pronged strategy. We craft questionnaires with precision to sidestep any client-induced bias. This involves avoiding leading questions or answers, offering a wide array of answer choices, maintaining a logical flow, and ensuring ethically sound research. They've also refined the provided questionnaire to minimize bias, as detailed in Appendix 1: Survey. Participant incentives are kept separate from the research-purchasing company.

3.1.2. Analysis of the selected survey variables

Table 1. Percentage of respondents who are not at all interested or not very interested in different blockchain trends

Panel a. Denmark

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>16 to 24</th>
<th>25 to 34</th>
<th>35 to 44</th>
<th>45 to 54</th>
<th>55 to 64</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Crypto</strong></td>
<td>61.40%</td>
<td>42.90%</td>
<td>42.80%</td>
<td>53.90%</td>
<td>77.40%</td>
<td>87.90%</td>
</tr>
<tr>
<td><strong>DeFi</strong></td>
<td>68.60%</td>
<td>53.40%</td>
<td>50.80%</td>
<td>61.30%</td>
<td>83.10%</td>
<td>92.20%</td>
</tr>
<tr>
<td><strong>NFTs</strong></td>
<td>66.90%</td>
<td>49.50%</td>
<td>53.10%</td>
<td>52.60%</td>
<td>83.20%</td>
<td>93.90%</td>
</tr>
<tr>
<td><strong>Stablecoins</strong></td>
<td>68.90%</td>
<td>52.10%</td>
<td>57.30%</td>
<td>61.40%</td>
<td>80.90%</td>
<td>91.30%</td>
</tr>
<tr>
<td><strong>Web3</strong></td>
<td>68.40%</td>
<td>55.20%</td>
<td>49.80%</td>
<td>58.80%</td>
<td>83.20%</td>
<td>92.90%</td>
</tr>
</tbody>
</table>

Panel b.: Finland

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>16 to 24</th>
<th>25 to 34</th>
<th>35 to 44</th>
<th>45 to 54</th>
<th>55 to 64</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Crypto</strong></td>
<td>54.70%</td>
<td>34.00%</td>
<td>47.30%</td>
<td>48.60%</td>
<td>68.10%</td>
<td>74.00%</td>
</tr>
<tr>
<td><strong>DeFi</strong></td>
<td>73.20%</td>
<td>66.80%</td>
<td>59.00%</td>
<td>75.40%</td>
<td>82.40%</td>
<td>81.40%</td>
</tr>
<tr>
<td><strong>NFTs</strong></td>
<td>68.80%</td>
<td>58.10%</td>
<td>54.90%</td>
<td>68.80%</td>
<td>79.40%</td>
<td>81.40%</td>
</tr>
<tr>
<td><strong>Stablecoins</strong></td>
<td>70.90%</td>
<td>59.00%</td>
<td>61.00%</td>
<td>68.90%</td>
<td>81.60%</td>
<td>82.40%</td>
</tr>
<tr>
<td><strong>Web3</strong></td>
<td>71.70%</td>
<td>58.80%</td>
<td>61.30%</td>
<td>73.20%</td>
<td>81.40%</td>
<td>82.40%</td>
</tr>
</tbody>
</table>
Table 1 presents the proportion of participants from Denmark, Finland, and Sweden who express no interest in several blockchain innovations, including Cryptocurrencies (Crypto), Decentralized Finance (DeFi), Non-Fungible Tokens (NFTs), Stablecoins, and Web3. This data is further segmented by age brackets.

Denmark consistently records the highest levels of disinterest in all blockchain innovations, with Finland trailing behind, and Sweden showing the least disinterest. To illustrate, in Denmark, 61.40% of participants are unenthusiastic about Crypto. This sentiment is shared by 54.70% in Finland and 51.80% in Sweden. Across these three countries, the age bracket of 55 to 64 consistently exhibits the most disinterest in all blockchain innovations. Conversely, the younger demographics, specifically the 16 to 24 and 25 to 34 age groups, display the least reservations, suggesting a greater receptiveness or willingness to delve into these blockchain realms. Crypto consistently stands out as the most familiar or accepted blockchain trend across all nations, as evidenced by its lowest disinterest percentages. On the other hand, DeFi and Web3 face higher levels of skepticism, hinting that they might be lesser-known or embraced by the general populace.

<table>
<thead>
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<th>35 to 44</th>
<th>45 to 54</th>
<th>55 to 64</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Crypto</strong></td>
<td>51.80%</td>
<td>40.20%</td>
<td>41.60%</td>
<td>42.90%</td>
<td>59.90%</td>
<td>75.10%</td>
</tr>
<tr>
<td><strong>DeFi</strong></td>
<td>63.60%</td>
<td>58.60%</td>
<td>56.50%</td>
<td>52.80%</td>
<td>70.80%</td>
<td>80.30%</td>
</tr>
<tr>
<td><strong>NFTs</strong></td>
<td>61.80%</td>
<td>50.80%</td>
<td>51.20%</td>
<td>53.00%</td>
<td>72.10%</td>
<td>82.80%</td>
</tr>
<tr>
<td><strong>Stablecoins</strong></td>
<td>62.30%</td>
<td>57.30%</td>
<td>51.20%</td>
<td>49.70%</td>
<td>72.80%</td>
<td>81.50%</td>
</tr>
<tr>
<td><strong>Web3</strong></td>
<td>63.30%</td>
<td>62.20%</td>
<td>53.30%</td>
<td>50.10%</td>
<td>70.80%</td>
<td>81.80%</td>
</tr>
</tbody>
</table>
Table 2 shows overall ownership of financial assets. It demonstrates that savings is the most common form of savings/investment, with 47.07% of the respondents indicating it. This is expected since traditional banking is one of the most accessible and widely-used financial services globally. These are the next most common investments, with 29.95% and 29.43% of the respondents indicating they have investments in mutual funds and stocks/shares, respectively. These forms of investments are popular due to the potential for higher returns compared to regular savings accounts. 29.23% of the respondents have pensions. Real Estate/Property is another significant form of investment, with 12.90% of respondents indicating they have investments in properties other than their primary residence. Interestingly, 11.06% of respondents indicate they own crypto assets or NFTs. This percentage is notable, given the relatively recent surge in popularity and understanding of these assets. Antiques/Art, Bonds, ESG products are less commonly held investments, each with less than 10% of respondents indicating ownership. A considerable 19.42% of respondents indicated they do not have any savings or investments. This segment of the population may represent those in earlier stages of their financial journey, those who prioritize consumption over saving, or those in financial hardship.
The analysis across age and gender, reveals that in general, females seem to have higher savings in the bank across all age groups compared to males. However, males seem to be more invested in stocks/shares and crypto assets.

Fig. 2. Distribution of crypto assets/NFT ownership by age

Fig 2. illustrates the distribution of crypto assets/NFTs ownership across various age groups. Ownership of crypto assets/NFTs is more prevalent among younger age groups, peaking in the 25-35 age range. There is a noticeable decline in ownership as age increases, with very few individuals above 60 owning crypto assets/NFTs. Among males, the age group 18-30 has the highest ownership of crypto assets/NFTs, followed by the 31-40 age group. This indicates that younger males are more inclined towards cryptocurrency investments. Among females, while the 18-30 age group has a relatively higher ownership of crypto assets/NFTs, the numbers are significantly lower compared to males in the same age group.

The distribution of crypto assets/NFTs ownership across various marital statuses is as follows (ordered by descending values): Married: 14.35%, In a relationship: 10.89%, Single: 10.40%, Other: 6.45%, Divorced/separated: 3.91%. Thus, it's interesting to note that individuals who are married have the highest rate of crypto assets/NFTs ownership, followed closely by those in a relationship and singles.
The distribution of crypto assets/NFTs ownership across various education levels shows the following:

![Distribution of Crypto Assets/NFTs Ownership Across Education Levels](image)

Fig. 3. Distribution of crypto assets/NFTs across education levels

Fig. 3 demonstrates, the majority of crypto owners have a University Undergraduate (Bachelor’s) degree, followed closely by those with a University Postgraduate (Master’s) degree. A significant proportion of crypto owners also have completed their Secondary School/High School. Fewer crypto owners have a PhD or have only Primary/Elementary education.

The dependent variable comes from the question, "I would like to have cryptos in the future?". Combining "somewhat agree" and "strongly agree" responses, ~27% of respondents want to hold cryptocurrencies in the future, though only about 25% correctly answered the basic question testing cryptocurrency knowledge.
Fig. 4. Distribution of the owners of crypto assets who intend to hold cryptocurrency in the future.

Fig. 4. illustrates the distribution of responses to the statement "I would like to hold cryptocurrency in the future" among respondents who currently own cryptocurrencies. A significant portion of cryptocurrency owners strongly agree (response 10) with the sentiment of wanting to hold cryptocurrencies in the future. The second most prevalent response is "9", indicating that a substantial number of crypto owners somewhat strongly agree with the sentiment. A smaller yet notable portion of respondents chose "I don't know" (response 11). Few respondents strongly disagree with holding cryptocurrencies in the future.

Breaking down the previous distribution based on their past experiences derives the following (Fig. 5):

Fig. 5. Distribution of sentiments about holding cryptocurrencies and past experiences.
Fig. 5. describes the distribution of sentiments about holding cryptocurrencies in the future, broken down by past experiences among cryptocurrency owners. Respondents who have gained in the past from their crypto investments seem to have a strong inclination towards holding cryptocurrencies in the future. The majority of them "completely agree" or "somewhat agree" with the sentiment. While a significant proportion of respondents who lost from past crypto investments also show a strong inclination towards future crypto holding, there's a noticeable spread across the sentiment spectrum compared to the "gained" group. Some of these respondents seem to be less optimistic about holding crypto in the future, though, nevertheless, we can see that an increase in losses is also associated with stronger desire to hold crypto assets in the future. Respondents who preferred not to disclose their past experience with crypto investments also predominantly agree with the sentiment of holding crypto in the future. These suggest that past experiences can play a role in shaping individuals' future intent regarding cryptocurrencies. Those who have lost exhibit a more varied range of sentiments.

In terms of past experience, we use the answers to the question: “Since you started investing, have you gained or made a loss on your crypto investments?”

Table 3. Cryptocurrency gains/losses

<table>
<thead>
<tr>
<th>Type</th>
<th>Totals</th>
<th>Male</th>
<th>Female</th>
<th>Denmark</th>
<th>Sweden</th>
<th>Finland</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gained</td>
<td>12.6%</td>
<td>19.9%</td>
<td>5.0%</td>
<td>13.9%</td>
<td>14.9%</td>
<td>6.7%</td>
</tr>
<tr>
<td>Lost</td>
<td>4.6%</td>
<td>6.4%</td>
<td>2.7%</td>
<td>5.5%</td>
<td>4.2%</td>
<td>4.2%</td>
</tr>
<tr>
<td>Prefer not to say</td>
<td>1.1%</td>
<td>1.2%</td>
<td>1.1%</td>
<td>1.6%</td>
<td>1.2%</td>
<td>0.4%</td>
</tr>
</tbody>
</table>

In terms of experience (Table 3), the results advise that males in Sweden have the highest percentage reporting gains from their crypto investments. Females in Finland report the lowest gains. Males in Denmark report the highest losses while females in Sweden report the lowest losses.
Gender dynamics in cryptocurrency investments seem to vary across countries. Males generally report higher gains compared to females. However, the losses are relatively evenly distributed between genders.

Linking together sentiments about future holding cryptocurrencies, past experiences and education level, derives the following:

Fig. 6. Heatmap of the average desire to hold cryptocurrency in the future ($q391$) by past experience and education level for current cryptocurrency owners.

Fig. 6 represents the average desire to hold cryptocurrency in the future ($q39=11$) by past experience and education level for current cryptocurrency owners. For those who gained in the past, we can say that across education levels, there's a noticeable inclination towards holding cryptocurrencies in the future, with postgraduate degree holders showing the strongest agreement. The desire is slightly weaker for those with only primary education. For those who lost in the past, there is a slightly weaker positive inclination towards holding cryptocurrencies in the future, with the highest agreement among those with an upper secondary education. Interestingly, those with postgraduate degrees who experienced losses in the past have a similar inclination towards future cryptocurrency holding as those who gained. Overall, past gains seem to have a positive influence on the desire to hold cryptocurrencies in the future across all education levels. However, past losses
don't deter individuals with higher education from considering future investments in cryptocurrencies.

We create an overconfidence categorical variable ranging from 0 to 2 using answers to the two following questions. The first question, "Which of the following are considered to be cryptos/tokens?" has five options, with option 4 being correct, i.e., 1) BTC, ETH, LTC, UNI, BYND, WMT, AAPL; 2) SNP, AMZN, PTR, AAPL, 3MSFT; 3) AAVE, USDP, AMZN; 4) BTC, ETH, ICP, WBTC, LEO, CRO, XLM; 5) I don't know.

![Distribution of Responses for Knowledge of Cryptos](image)

Fig. 7. Distribution of responses for knowledge of crypto assets (the correct answer is 4).

The second question, "I have a strong understanding of cryptocurrencies," has six options ranging from "strongly disagree" to "not applicable/don't know."

![Distribution of Responses for "I have a strong understanding of cryptocurrencies"](image)

Fig. 8. Distribution of responses for the “I have a strong understanding of cryptocurrencies” question
The overconfidence variable equals 1 if a respondent answers the first question incorrectly but somewhat agrees to having strong cryptocurrency knowledge, and 2 if they strongly agree to having strong cryptocurrency knowledge. In other cases, overconfidence is 0.

![Distribution of Overconfidence Levels](image)

Fig. 9. Distribution of overconfidence level.

Overall, the distribution of overconfidence among respondents who have invested in crypto assets/NFTs (Fig. 8) is as follows: approximately 70.24% of respondents are not overconfident. Approximately 20.24% of respondents are somewhat (moderately) overconfident, while approximately 9.52% of respondents are strongly overconfident.

*Economic expectations and holding of cryptos*

![Economic Expectations](image)

Fig. 10. Over the next year, what do you think will happen to the prices for the following?
Based on Fig. 10, in terms of petrol, most respondents expect the prices to "Increase slightly" or "Increase dramatically". A smaller proportion believes prices will "Stay the same", and very few expect a decrease.

Regarding Groceries, the majority expect prices to "Increase slightly". This is followed by those who expect prices to "Stay the same" or "Increase dramatically". Again, very few expect a decrease. The trend in Utility bills is similar to groceries with a majority expecting a slight increase, followed by those expecting prices to remain the same or increase dramatically.

In terms of stocks, the opinions are more spread out. A significant proportion expects stock prices to "Increase slightly", but there's also a notable amount of uncertainty with many respondents selecting "Do not know".

And finally Cryptos - the distribution here is quite diverse. A significant number of respondents expect prices to "Increase slightly" or "Stay the same". However, there's a larger uncertainty compared to other categories, with many choosing "Do not know".

Averal, a good number of respondents chose "Do not know", indicating uncertainty about the future of crypto prices. These insights provide a snapshot of the general sentiment regarding the future prices of different items and assets. Respondents largely expect inflation in essentials like petrol, groceries, and utilities, while having varied opinions on stocks and cryptocurrencies.
Fig 11a. Average responses for the price expectations questions based on a current asset ownership

Fig. 11b. Price expectations vs future asset ownership

Fig 11a displays the average response values for the "q44" questions, based on the types of savings/investments respondents have (from the "q10" question). Respondents with Pensions, Real

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Estate, and Savings in the bank generally have a similar pattern in their expectations across all the "q44" categories. They tend to expect prices to increase slightly. Respondents with stocks/shares as their investment show a slightly higher expectation of stock prices increasing, which makes intuitive sense. They also have a noticeable expectation of crypto prices increasing.

The group of Crypto assets / NFTs owners has a distinct pattern. They show a higher expectation of crypto prices increasing compared to other investment types. They also have a slightly more bullish view on stock prices. Respondents in Antiques/Art, Bonds, and Mutual funds categories show patterns similar to the general population, with a tendency towards expecting prices to increase slightly in most "q44" categories.

ESG products and “Other” groups have varied expectations, but again, there’s a general tendency towards expecting prices to increase slightly.

Prefer not to say group's expectations are generally aligned with the broader population. And finally, respondents without any savings or investments tend to have a slightly more conservative view, especially regarding cryptos.

Fig 11b displays the distribution of responses regarding price expectations (q44_ questions: “Over the next year, what do you think will happen to the prices for the following?”) for various items and assets over the next year, based on the sentiment towards holding. The results show, that irrespectively of their expectation on petrol prices, respondents generally have a similar sentiment towards holding cryptocurrencies. Those expecting a dramatic increase in petrol prices show slightly more inclination towards holding cryptos. Expectations about grocery prices show minor variations in the sentiment towards holding cryptos. Respondents expecting grocery prices to "Increase dramatically" seem to have a slightly stronger inclination towards holding cryptos. The sentiment towards cryptos is relatively consistent across different expectations for utility bills. Respondents expecting stock prices to "Increase dramatically" or "Decrease dramatically" have a stronger inclination towards holding cryptos compared to those with milder expectations. As expected,
respondents who believe crypto prices will "increase dramatically" are highly inclined to hold cryptos in the future. Conversely, those who expect a decrease in crypto prices are less inclined.

In terms of general macroeconomic expectations, they are as follows (Fig. 12):

*Change in total income due to price changes (q45):* A significant portion of respondents expect their total income to be around the same as the current prices. Many also believe their total income will be less than the current prices. Only a small fraction expects their income to exceed current prices, and a similar small proportion are uncertain.
Expectation of savings in the next year (q46): The majority of respondents anticipate having the same amount of savings next year as they currently have. A significant number also expect to have more savings. Fewer respondents believe they will have less savings, and a small portion are uncertain.

Expectation for economic situation (q47): A substantial number of respondents believe the economic situation will remain the same in the coming year. Many also think the situation will get a little better, while a similar number expect it to get a little worse. Fewer respondents are highly pessimistic (expecting it to get a lot worse) or highly optimistic (expecting it to get a lot better). A small portion of respondents are unsure about the economic outlook.

3.2. Model

We employ multinomial survey-weighted generalised linear models with inverse-probability weighting and design-based standard errors following Lumley and Scott (2017).

A GLM relates a linear predictor to the response variable through a link function. It’s given by:

\[ g(E[Y_i]) = x_i^T \beta \]  

(1)

where \( g(\cdot) \) is the logit link function, \( E[Y_i] \) is the expected value \( \mu_i \) of the response variable that is the responses to the statement “I would like to hold cryptocurrency in the future” (with the categories: 1 - Strongly disagree, 2 - Somewhat disagree, 3 - Neither agree nor disagree, 4 - Somewhat agree, 5 - Strongly Agree, 6 - Not applicable/Don't know) for the \( i \)-th observation, \( x_i \) is the vector of predictors for the \( i \)-th observation. All predictors are provided in Appendix, though in this study we focus on the responses to the statement “Since you started investing, have you gained or made a loss on your crypto investments?” with the following categories: 1 – Gained, 2 – Lost, 3 - Prefer not to say. \( \beta \) is the vector of coefficients.
In our study a multinomial model for nominal response variables with more than two levels. In this model, the probabilities of the different outcomes (or categories) of the response variable are related to the predictors through the multinomial logit link function.

Given $J$ categories for the response variable “I would like to hold cryptocurrency in the future”, with one category (often the last one, $J$) taken as the reference, the multinomial logit link for category $j$ is defined as $\log \left( \frac{P(Y=j)}{P(Y=J)} \right) = x^T \beta_j$ for $j=1,2,...,J-1$, where $P(Y=j)$ is the probability that the response falls into category $j$, $x$ is the vector of predictors, $\beta_j$ is the vector of coefficients for category $j$.

Inverse-probability weights (often derived from the inverse of the probability of being sampled) adjust the model for unequal probabilities of selection. Let's denote these weights as $w_i$ for observation $i$. The weighted log-likelihood for observation $i$ is:

$$L_i(\beta) = w_i \cdot \log \left( P(Y_i = j \mid x_i, \beta_j) \right)$$

(2)

Where $w_i$ is the inverse-probability weight for observation $i$ and is typically defined as the inverse of the probability of observing that particular data point given the characteristics as respondents age, gender, education profile etc.\(^4\) The overall weighted log-likelihood is the sum of $L_i(\beta)$ over all observations.

For complex survey designs, especially those involving stratification and clustering, as in our case\(^5\), standard errors need to be adjusted. One common method is Taylor linearization, which approximates the variance of the estimator by linearizing around the estimated coefficients.

Using Taylor linearization, the design-based variance for a coefficient $\hat{\beta}$ can be approximated as:

$$\text{Var}(\hat{\beta}) \approx X^T W X$$

(3)

\(^4\) After fieldwork, GWI assigned a “weight” to every respondent. The average weight a respondent receives varies by market, and is largely influenced by the size of the population in that country, as well as the ease of conducting research there.

\(^5\) Each stratum (country) and each category of the selected statement.
where $X$ is the design matrix, $W$ is a diagonal matrix of survey weights, $V$ is a diagonal matrix of residuals.

4. Empirical results

4.1. Exploratory analysis

We start with understanding relationship between overconfidence and crypto-currency ownership. Based on the chi-squared test of independence between overconfidence and having crypto assets/NFTs\(^6\) we can reject the null hypothesis that having crypto assets/NFTs is independent of overconfidence. This suggests that there is a significant association between overconfidence levels and the likelihood of owning crypto assets/NFTs. We also estimate the relationship between overconfidence and the average amounts invested in cryptocurrency per month\(^7\). The low $p$-values for all three countries suggest that there's a statistically significant association between overconfidence levels and amount invested into crypto asset for three countries.

The next step is to estimate correlations. The Cramér's $V$ values for the association between overconfidence and the invested amount for each country indicate the positive, though not high coloration (Finland: Cramér's $V = 0.177$, Denmark: Cramér's $V = 0.150$, Sweden: Cramér's $V = 0.199$).

We used the ANOVA test to determine if there's a statistically significant difference in the average units held of each cryptocurrency between different levels of overconfidence. The $p$-value tells us whether these differences are statistically significant. For this purpose we use the answer to the question: How many crypto units you currently hold?. Table 4 below summarizes the estimates:

---

\(^6\) Chi-squared Statistic: 74.41, $p$-value: $6.94 \times 10^{-17}$

\(^7\) Finland: $p$-value = $4.81 \times 10^{-15}$; Denmark: $p$-value = $3.27 \times 10^{-10}$; Sweden: $p$-value = $1.67 \times 10^{-19}$
Table 4. Anova test results for average units held of cryptocurrencies for each level of overconfidence (sorted by p values)

<table>
<thead>
<tr>
<th>Cryptocurrency</th>
<th>Anova p-value</th>
<th>Average units held for each level of overconfidence (0, 1, and 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Avalanche (AVAX)</td>
<td>2.56E-09</td>
<td>0.36</td>
</tr>
<tr>
<td>Bitcoin SV (BSV)</td>
<td>1.31E-08</td>
<td>0.27</td>
</tr>
<tr>
<td>Filecoin (FIL)</td>
<td>8.89E-08</td>
<td>0.01</td>
</tr>
<tr>
<td>Nem (XEM)</td>
<td>1.24E-07</td>
<td>0.28</td>
</tr>
<tr>
<td>Dogecoin (DOGE)</td>
<td>1.94E-07</td>
<td>157.73</td>
</tr>
<tr>
<td>Nano</td>
<td>2.14E-07</td>
<td>0.95</td>
</tr>
<tr>
<td>Neo</td>
<td>1.38E-06</td>
<td>0.38</td>
</tr>
<tr>
<td>Celsius (CEL)</td>
<td>1.40E-06</td>
<td>0.09</td>
</tr>
<tr>
<td>Binance Coin (BNB)</td>
<td>4.19E-06</td>
<td>2.14</td>
</tr>
<tr>
<td>XRP (XRP)</td>
<td>5.66E-05</td>
<td>8.76</td>
</tr>
<tr>
<td>Ethereum (ETH)</td>
<td>0.00032</td>
<td>4.98</td>
</tr>
<tr>
<td>Stellar (XLM)</td>
<td>0.001592</td>
<td>5.05</td>
</tr>
<tr>
<td>U.S Dollar Coin (USDC)</td>
<td>0.001711</td>
<td>9.87</td>
</tr>
<tr>
<td>Polkadot (DOT)</td>
<td>0.001781</td>
<td>0.18</td>
</tr>
<tr>
<td>EOS Coin (EOS)</td>
<td>0.007215</td>
<td>6.84</td>
</tr>
<tr>
<td>Tron (TRX)</td>
<td>0.009794</td>
<td>38.84</td>
</tr>
<tr>
<td>VeChain (VET)</td>
<td>0.018258</td>
<td>3.36</td>
</tr>
<tr>
<td>Tether (USDT)</td>
<td>0.118207</td>
<td>28.94</td>
</tr>
<tr>
<td>Cosmos (ATOM)</td>
<td>0.189473</td>
<td>0.67</td>
</tr>
<tr>
<td>Zcash (ZEC)</td>
<td>0.294353</td>
<td>0.44</td>
</tr>
<tr>
<td>Cardano (ADA)</td>
<td>0.683562</td>
<td>9.29</td>
</tr>
<tr>
<td>Dash (DASH)</td>
<td>0.824458</td>
<td>4.48</td>
</tr>
<tr>
<td>Dai (DAI)</td>
<td>0.949292</td>
<td>1.58</td>
</tr>
<tr>
<td>Bitcoin (BTC)</td>
<td>0.951059</td>
<td>8.51</td>
</tr>
<tr>
<td>Other</td>
<td>0.952887</td>
<td>1876.42</td>
</tr>
<tr>
<td>Solana (SOL)</td>
<td>0.953491</td>
<td>11.96</td>
</tr>
</tbody>
</table>

Table 4 shows that for Bitcoin (BTC), Ethereum (ETH), and many other cryptocurrencies there's a statistically significant association between overconfidence and the average units held for these cryptocurrencies. This is indicated by their low p-values. The average units held for each level of overconfidence demonstrate, that on average, higher overconfidence is associated with higher amount of cryptocurrencies held.
For Tether (USDT), Cosmos (ATOM), Zcash (ZEC), Cardano (ADA), Dash (DASH), Dai (DAI), Bitcoin (BTC), and Solana (SOL) the p-values for these cryptocurrencies are higher than 0.05, suggesting no significant difference in average units held across overconfidence levels. This means that overconfidence does not seem to play a major role in determining the number of units of these cryptocurrencies held by individuals.

Fig. 13. Distribution of responses for “I would like to know more about cryptocurrencies” and overconfidence levels for crypto-asset owners.

Fig. 13. Demonstrates that “Strongly Agree” and “Somewhat Agree” are dominant responses across all levels of overconfidence. This reiterates that among those who own cryptocurrencies, there's a strong interest in learning more about them. Respondents with “High Overconfidence” have a prominent count in the "Strongly Agree" category, suggesting that even those who perceive themselves as highly knowledgeable are keen on enhancing their understanding. The observation that higher overconfidence doesn't diminish the interest in gaining more knowledge about cryptocurrencies can be considered surprising because overconfidence often implies that an individual believes they already possess a high level of knowledge or expertise. With such a belief,
one might expect them to feel less need to learn more or further educate themselves. However, the data suggests otherwise, and this counterintuitive finding can be interpreted in a few ways.

First, cryptocurrencies and the associated technologies (like blockchain) are rapidly evolving fields. Even those who are highly confident about their current knowledge might recognize the dynamic nature of the field and see the value in continuously updating their understanding. Second, those who are overconfident might also be the most bullish about the potential of cryptocurrencies. As a result, their eagerness to learn more could be driven by their belief in the future importance and ubiquity of these digital assets. Third, the boundary between confidence in one's knowledge and the desire to learn more isn't always clear-cut. It's possible for someone to both believe they know a lot and simultaneously recognize that there's much more to learn, especially in a complex domain like cryptocurrencies. Forth, the Dunning-Kruger Effect that is a cognitive bias where people with low ability or knowledge overestimate their ability. In this context, individuals might believe they know a lot (overconfidence) but also recognize gaps in their understanding, leading them to want to learn more. And finally, those who are overconfident might also be heavily invested in cryptocurrencies. Their desire to learn more might be driven by a financial interest in understanding market dynamics, technological advancements, and other factors that could impact their investments.

Fig. 14. Distribution of past trade experience across overconfidence levels for crypto-asset owners
Fig. 14 shows the association between overconfidence and the responses related to the past experience (gains/losses). It demonstrates that 54% of strongly overconfident gained while only 14.5% of the strongly overconfident lost. Thus, it's interesting to see that even among those who lost money in cryptocurrencies, there's a significant presence of overconfidence and even strong overconfidence. This could be a demonstration of various behavioral biases, such as the endowment effect (overvaluing what we own) or confirmation bias (favoring information that confirms our pre-existing beliefs, and dismissing information that contradicts them). Notably, those who gained in the past have a higher proportion of strong overconfidence compared to those who lost, suggesting that past successes might amplify overconfidence, which aligns with behavioral finance theories.

The data suggests that even past experiences (like gains or losses) might not deter some individuals from being overconfident. In behavioral finance, overconfidence can lead individuals to believe they have superior trading skills or market knowledge. This belief can make them trade more often, thinking they can outperform the market, which can lead to suboptimal investment outcomes. The analysis of answers to question (q34) - “How often do you trade?” (Several times per day, Once per day, Once per week, Several times per week, Once per month, Several times per month, Several times per year, Once per year) shows the following pattern (Fig. 15):
Fig. 15. Distribution of trading frequencies across overconfidence levels for crypto-asset owners

Fig.15 demonstrates, that overconfidence, both mild and especially strong, seems to be associated with a higher frequency of trading, especially on a weekly basis. This aligns with behavioral finance theory (e.g., Barber and Odean, 2000), which suggests that overconfident investors might trade more frequently, believing that their knowledge or ability gives them an edge. Those with no overconfidence seem to trade less frequently than their overconfident counterparts, potentially indicative of a more cautious approach or a recognition of the risks associated with frequent trading.

It's worth noting that trading frequently doesn't necessarily equate to better investment outcomes. In fact, overtrading, driven by overconfidence, can often result in higher transaction costs and potentially suboptimal investment decisions.

Finally, linking together past experience, overconfidence and sentiments about desire to hold cryptocurrency derives the following heatmap (Fig. 16):
Fig. 16. Heatmap of experience, overconfidence and sentiments about desire to hold cryptocurrency in the future.

Fig. 16 shows the relationships between the desire to hold cryptocurrencies in the future (q39_1), past experiences with cryptocurrencies (q32), and overconfidence among current cryptocurrency owners. From the heatmap, we can make several observations. First, for no overconfident respondents with no past experience (q32 = 0) an average score is approximately 5.05, indicating a neutral stance on holding cryptocurrencies in the future. Those who gained from past crypto investments (q32 = 1) are more inclined to hold cryptocurrencies in the future, with an average score of 7.51. Those who lost from past crypto investments (q32 = 2) also show a similar inclination, with an average score of 7.38.

For the overconfident respondents (Overconfidence = 1) the pattern is different. Thus, overconfident respondents with no past experience show a slightly increased inclination to hold cryptocurrencies (average score of 5.69). Overconfident gainers and losers from past crypto investments show average scores of 7.44 and 8.77, respectively. Interestingly, overconfident
individuals who've faced losses but are overconfident have the highest inclination to invest in the future among this group.

For the strongly overconfident crypto investors who have no past experience or who prefer not to disclose have average scores of 5.5 and 7, respectively. Strongly overconfident gainers are more inclined to hold with an average score of 7.65. The strong overconfident group who faced losses in the past have a slightly lower inclination to hold cryptocurrencies in the future, averaging at quite high level of 6.71.

Those observations reveal some intriguing behavioral tendencies among cryptocurrency owners. Observing the highest desire to hold cryptocurrencies among individuals with past gains and strong overconfidence aligns with the Overconfidence Bias (Odean, 1998; Barber and Odean, 2021). Overconfidence Bias suggests that individuals tend to overestimate their knowledge, abilities, and the precision of their beliefs. In the context of investments, those who have seen past successes may overestimate their investing skills, attributing their past success to their skill rather than luck. This could lead to a heightened desire to continue investing, expecting positive outcomes in the future.

The high desire to hold cryptocurrencies among those with strong overconfidence, even after experiencing losses, can be attributed to the Self-serving Bias (Miller and Ross, 1975; Campbell and Sedikides, 1999). This bias refers to the tendency to attribute positive events to one's own character but attribute negative events to external factors. In this case, individuals might attribute their losses to external market factors, volatile nature of the asset, or other investors' behaviors, while still believing in their own investment acumen. This cognitive dissonance allows them to maintain their confidence and desire to invest.

In the overconfident group, those who've previously faced losses and exhibit the highest desire to invest in cryptocurrencies in the future can be also explained by the "gambler's fallacy" or a belief that their luck will turn around.
Those with no overconfidence, regardless of past experiences, showing a relatively lower desire to invest in cryptocurrencies can be seen through the lens of Loss Aversion (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). Loss Aversion, a key concept in Prospect Theory, suggests that people feel the pain of losing money more intensely than they feel the pleasure of gaining. Without the cushion of overconfidence, individuals might be more cautious due to the inherent volatility and risk of cryptocurrencies.

The fact that overconfidence seems to have a significant influence on the desire to hold cryptocurrencies, even in the face of past losses, can also be explained by the Endowment Effect (Thaler, 1980; Kahneman et al. 1991). People often ascribe more value to things merely because they own them. Coupled with overconfidence, cryptocurrency owners might believe that the assets they hold have a higher value or potential than they might objectively have, making them more inclined to hold onto them.

4.2. Economic optimism

To determine which asset owners are the most optimistic, we set criteria for optimism based on the questions we analyzed:

- For q45 (Change in total income due to price changes): Optimism would be reflected by the belief that one's total income will be more than the current prices.
- For q46 (Expectation of savings in the next year): Optimism would be indicated by the expectation to have more savings.
- For q47 (Expectation for the economic situation): Optimism would be demonstrated by the belief that the economic situation will get a little better or a lot better.
Fig. 17a. Average economic optimism score per country

Fig. 17b. Average economic optimism score by marital status, with the size of each marker indicating the number of respondents in that category.

Fig. 17c. Average economic optimism score by the number of dependents.

Note: The color intensity represents the number of respondents, with darker colors indicating more respondents. The marker size also helps visualize the number of respondents in each category.
Fig. 17d. Average economic optimism score by education level.
Note: The size of each marker indicates the number of respondents in that category, while the color intensity represents the number of respondents, with darker shades indicating more respondents.

Fig. 17e. Average economic optimism score by household income per country.
Fig 17a demonstrates that that respondents from Denmark are, on average, more optimistic than those from Sweden and Finland. Fig 17b shows that being in a relationship or married seems to be associated with a higher level of optimism compared to being divorced/separated, that is expected. Fig. 17c suggests that having one dependent seems to correlate with the highest level of optimism. As the number of dependents increases, the optimism score appears to decrease slightly, though there’s an uptick for those with more than three dependents. From Fig 17d we can see that individuals with postgraduate degrees (both Master's and PhD) tend to be more optimistic than other education levels. This could be due to various factors, including a higher level of knowledge, financial stability, or job security associated with higher educational qualifications. Fig. 17e demonstrates an absence of a pattern that link higher income with higher economic optimism.

Given the criteria of happiness, we calculate an optimism score for each asset type by summing the proportions of optimistic responses from each question. The asset type with the highest optimism score will be deemed the most optimistic.

![Optimism Score by Asset Type](https://ssrn.com/abstract=4616047)

**Fig 18. Optimism vs asset ownership**

Fig 18 shows that owners of ESG products are the most optimistic, with the highest optimism score. This is followed closely by owners of Crypto assets / NFTs and Antiques / Art. Owners of Bonds and those who specified Other types of assets also show a high level of optimism.
On the other end of the spectrum, respondents who selected "No savings/investments" and "Prefer not to say" exhibit the lowest levels of optimism.

To address the potential bias of more male investors, we normalize the optimism scores by the total number of respondents of each gender within each asset type. This gives us a "per capita" optimism score, allowing for a fair comparison between males and females. Thus, "normalization" in this context means adjusting the optimism scores to account for the differing number of male and female respondents within each asset category. We perform the following steps:

Filter Data: For each asset type, we separate the data into two groups: male respondents and female respondents.

Calculate Raw Optimism Score: For each gender group and asset type, we calculate the raw optimism score. This was done by checking the proportion of optimistic responses, as defined by our criteria, for the questions q45, q46, and q47. For each asset type $A$ and gender $G$, the raw optimism score $S_{raw}$ is calculated as:

$$S_{raw}(A, G) = \sum_{i=1}^{n} O(Q_i, G)$$

Where: $n$ is the number of questions (in our case, 3: q45, q46, q47), $O(Q_i, G)$ is the proportion of optimistic responses for question $Q_i$ for gender $G$. It's a value between 0 and 1, with 1 indicating 100% optimistic responses.

Normalize: The raw optimism score was then divided by the total number of respondents of that gender within the asset type. This gives an average or "per capita" optimism score for each gender in each asset category. The normalized or "per capita" optimism score $S_{norm}$ is:

$$S_{norm}(A, G) = \frac{S_{raw}(A, G)}{T(A, G)}$$

Where $T(A, G)$ is the total number of respondents of gender $G$ for asset type $A$.

This "per capita" optimism score tells us, on average, how optimistic each individual is within a gender group, for each asset type. By using this normalized score, we can fairly compare
optimism between males and females without the results being skewed by the sheer number of respondents from one gender.

Fig. 19. “Normalized” optimism score (accounting for imbalance in the number of respondents between categories or groups).

Fig 19 shows "micro" view, indicating the average sentiment of individuals within each category. For most asset types, the optimism levels between males and females are relatively close. However, in categories like Crypto assets / NFTs, Antiques/Art, and ESG products, females are more optimistic on a per capita basis than males. In contrast, for assets like Pensions, Real estate/property, Savings in the bank, and Stocks/shares, males tend to be more optimistic.

4.3. Model estimates

The estimates are provided in the table below:

Table 5. the multivariate GLM estimates on survey design.

| Panel a: Dependent variable is "I would like to hold cryptocurrency in the future: Strongly disagree" |
| Variable                                      | Estimate | Std.Error | z_value | Pr_\(z\) |
| Gained                                        | 3.773    | 2.243     | 1.682   | 0.093    |
| Lost                                          | 2.756    | 1.914     | 1.440   | 0.150    |
| Prefer not to say about losts/gains           | -2.287   | 2.183     | -1.048  | 0.295    |
| Overconfidence - 1                            | -0.264   | 0.811     | -0.326  | 0.745    |
| Overconfidence - 2                            | -16.851  | 5.175     | -3.257  | 0.001    |

| Panel b: Dependent variable is "I would like to hold cryptocurrency in the future: Somewhat disagree" |

Electronic copy available at: https://ssrn.com/abstract=4616047
### Panel c: Dependent variable is "I would like to hold cryptocurrency in the future: Neither agree nor disagree"

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>z_value</th>
<th>Pr_z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gained</td>
<td>-1.697</td>
<td>0.568</td>
<td>-2.985</td>
<td>0.003</td>
</tr>
<tr>
<td>Lost</td>
<td>-1.242</td>
<td>0.715</td>
<td>-1.737</td>
<td>0.083</td>
</tr>
<tr>
<td>Prefer not to say about losts/gains</td>
<td>-2.355</td>
<td>0.974</td>
<td>-2.419</td>
<td>0.016</td>
</tr>
<tr>
<td>Overconfidence - 1</td>
<td>-0.882</td>
<td>0.500</td>
<td>-1.765</td>
<td>0.078</td>
</tr>
<tr>
<td>Overconfidence - 2</td>
<td>0.470</td>
<td>0.757</td>
<td>0.621</td>
<td>0.535</td>
</tr>
</tbody>
</table>

### Panel d: Dependent variable is "I would like to hold cryptocurrency in the future: Somewhat agree"

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>z_value</th>
<th>Pr_z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gained</td>
<td>2.47E+14</td>
<td>3.02E+14</td>
<td>0.819</td>
<td>0.413</td>
</tr>
<tr>
<td>Lost</td>
<td>-1.2E+14</td>
<td>3.67E+14</td>
<td>-0.320</td>
<td>0.749</td>
</tr>
<tr>
<td>Prefer not to say about losts/gains</td>
<td>2.61E+14</td>
<td>4.6E+14</td>
<td>0.568</td>
<td>0.570</td>
</tr>
<tr>
<td>Overconfidence - 1</td>
<td>9.33E+13</td>
<td>2.44E+14</td>
<td>0.382</td>
<td>0.703</td>
</tr>
<tr>
<td>Overconfidence - 2</td>
<td>-1.4E+14</td>
<td>3.21E+14</td>
<td>-0.436</td>
<td>0.663</td>
</tr>
</tbody>
</table>

### Panel e: Dependent variable is "I would like to hold cryptocurrency in the future: Strongly Agree"

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>z_value</th>
<th>Pr_z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gained</td>
<td>-5.582</td>
<td>0.965</td>
<td>-5.782</td>
<td>0.000</td>
</tr>
<tr>
<td>Lost</td>
<td>25.601</td>
<td>1.039</td>
<td>24.640</td>
<td>0.000</td>
</tr>
<tr>
<td>Prefer not to say about losts/gains</td>
<td>145.157</td>
<td>1.526</td>
<td>95.139</td>
<td>0.000</td>
</tr>
<tr>
<td>Overconfidence - 1</td>
<td>27.313</td>
<td>0.651</td>
<td>41.961</td>
<td>0.000</td>
</tr>
<tr>
<td>Overconfidence - 2</td>
<td>88.176</td>
<td>0.948</td>
<td>93.005</td>
<td>0.000</td>
</tr>
</tbody>
</table>

### Panel f: Dependent variable is "I would like to hold cryptocurrency in the future: Don't know"

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>z_value</th>
<th>Pr_z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gained</td>
<td>10.718</td>
<td>1.368</td>
<td>7.833</td>
<td>0.000</td>
</tr>
<tr>
<td>Lost</td>
<td>14.154</td>
<td>1.576</td>
<td>8.980</td>
<td>0.000</td>
</tr>
<tr>
<td>Prefer not to say about losts/gains</td>
<td>-121.864</td>
<td>3.102</td>
<td>-39.282</td>
<td>0.000</td>
</tr>
<tr>
<td>Overconfidence - 1</td>
<td>23.836</td>
<td>0.873</td>
<td>27.307</td>
<td>0.000</td>
</tr>
<tr>
<td>Overconfidence - 2</td>
<td>13.480</td>
<td>1.496</td>
<td>9.011</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Note:** All the estimates can be provided on request due to the number of estimates. It includes additional factors influencing future market participation. For example, the unregulated nature and higher volatility of crypto prices negatively impact ownership intention, whereas holding cryptocurrencies for emergencies or cross-border/domestic transfers have a positive, statistically significant effect in the three Nordic countries.

Electronic copy available at: https://ssrn.com/abstract=4616047
For category 1 “Strongly Disagree” of the statement “I would like to hold cryptocurrency in the future”, the results indicate that individuals who have lost in past crypto transactions \((q32=2)\) do not significantly differ in strongly disagreeing with \(q23_1\). This might be due to the effect of loss aversion. After incurring a loss, they are not willing to take the risk again, which is in line with Kahneman and Tversky's Prospect Theory (Kahneman and Tversky, 1979). Overconfident individuals tend to strongly disagree with the statement: the estimated coefficient for overconfidence \(= 1\) equals -13.3 and is statistically significant. For strongly overconfident individuals the effect is also negative though is not statistically significant.

For category Category 2: “Somewhat Disagree” with the statement “I would like to hold cryptocurrency in the future” past experience has no statistical significant effect, while overconfidence continues having a negative impact with statistically significant negative effect from strong overconfidence.

For the neutral category “Neither Agree nor Disagree” to hold crypto assets in the future, neither past experience with cryptocurrencies nor overconfidence levels seem to play a significant role.

For the target category 5: “Strongly Agree” to hold crypto assets in the future, for respondents who have gained in their past cryptocurrency investments \((q32=1)\), the estimates are generally positive, suggesting that this group tends to have a more positive response (towards agreeing) to the future holding of crypto assets.

Respondents who have lost in their past cryptocurrency investments \((q32=2)\) show varying patterns, but in some response categories, particularly "Somewhat Agree" and "Strongly Agree" regarding sentiments about future holding of cryptos, they show a more positive response, which is somewhat surprising, implying that individuals who have incurred losses in the past are more likely to willing to hold own crypto-assets. The results suggest that individuals who have incurred losses in the past with cryptocurrencies are more likely to agree with the statement “I would like to hold cryptocurrency in the future”. This could be explained by the Loss Aversion theory, which posits...
that people tend to prefer avoiding losses to acquiring equivalent gains. After incurring a loss, individuals might be motivated to continue investing in cryptocurrencies to recover their losses (Thaler and Johnson, 1990).

Respondents who are overconfident (overconfidence=1) tend to have positive estimates, particularly in the "Strongly Agree" category for the future cryptocurrency ownership sentiments. This suggests that overconfident respondents are more likely to strongly agree with the statement in the dependent variable.

Respondents who are strongly overconfident (overconfidence=2) do not show a clear pattern across different response categories, though, for the respondents you demonstrate strong desire to have cryptocurrencies in the future strong overconfidence has a positive statistical significant effect. This is consistent with the theory that overconfident investors are more likely to trade more and take more risks (Odean, 1998).

Thus, individuals who face losses in the past seem more inclined to want to invest in cryptocurrencies in the future. This could be seen as evidence of the Gambler’s Fallacy, where people believe that a series of losses increases the chances of a win in the future. Those who gained in the past, interestingly, show mixed responses across different future intentions. One possible explanation could be the "house money effect", where people are more willing to take risks with gains they perceive as "house money" (Thaler and Johnson, 1990).

Overconfidence, as expected, plays a significant role, especially in the extreme categories (Strongly Disagree, Strongly Agree). Overconfident investors tend to overestimate the quality of their own information and underestimate investment risk (Guiso and Jappelli, 2006). This seems evident in the strong inclination to hold cryptocurrencies in the future among the highly overconfident.

Those who prefer not to disclose their past experiences show a stronger inclination to hold or are uncertain about holding cryptocurrencies in the future. This could be indicative of some
underlying factors or biases that are influencing their decision-making but are not captured directly in the data.

![ROC curve](image)

Fig. 13. ROC curve

In Fig. 13, we plot the true positive rate (sensitivity) against the false positive rate (1-specificity) for different cutoff points, ranging from 0 to 1, regarding the probability of future cryptocurrency ownership. According to Hosmer & Lemeshow (2000), classifiers with curves closer to the top-left corner, as in our case, indicate high performance (sensitivity=1 and false positive rate=0), supporting the quality of our findings.

5. Conclusion
This paper examines the effect of past experience and overconfidence on future cryptocurrency ownership in three Nordic countries, by applying GLMs to recent unique survey data. Our research makes contributions to several streams of literature, enhancing our understanding of cryptocurrency market investor behavior.
First and foremost, we contribute a nuanced perspective on the influence of cognitive biases on investor behavior in these markets. Notably, our findings reveal an intriguing divergence between the behaviors of cryptocurrency and traditional market participants. Specifically, we uncover that negative past experiences with investments increase the likelihood of future cryptocurrency ownership, suggesting that crypto investors with adverse past experiences may be more willing to take risks. This is in contrast to investor behaviour in traditional markets (Nofsinger, 2005). This finding also runs counter to those presented by Malmendier and Nagel (2011) and suggests a unique propensity among cryptocurrency investors for heightened risk-taking following past investment losses.

Second, we identify a potentially significant behavioral bias among crypto investors who have endured past losses. Despite these setbacks, a persistent desire to invest in the future, especially when overconfident, could be indicative of a self-serving bias (Miller and Ross, 1975; Campbell and Sedikides, 1999). These investors may attribute their past losses to external factors, such as market volatility, rather than their own decision-making, thereby maintaining their confidence in future investments.

Third, our finding that overconfidence increases the likelihood of holding cryptocurrencies in the future is consistent with previous research linking overconfidence to increased risk-taking and poor financial outcomes (Odean, 1998; Barber and Odean, 2000; Gervais & Odean, 2001). We empirically confirm that overconfidence significantly augments the likelihood of future cryptocurrency ownership. This aligns with the findings of Guiso and Jappelli (2006), reinforcing the notion that overconfident investors may overvalue their personal information quality and undervalue investment risk. Remarkably, our analysis reveals that this overconfidence effect is pervasive; even individuals who have sustained past losses, if overconfident, express a strong inclination to continue holding cryptocurrencies in the future.

Fourth, we find a compelling association between high levels of overconfidence and increased trading frequency, notably with a tendency for multiple daily trades. This observation
may be indicative of overconfident investors’ belief in their ability to outperform the market, thus engaging in more frequent trading. This behavior echoes findings in the broader behavioral finance literature, where overconfidence has been identified as a driver of heightened trading activity (Barber and Odean, 2000).

Fifth, our research deepens the literature on the role of personal experiences in shaping risk-taking behavior, particularly within the high-stakes domain of cryptocurrencies, thus complementing works like Malmendier and Nagel (2011).

Lastly, our findings cast a revealing light on the intricate relationship between gender, age, and overconfidence within the cryptocurrency markets, which are notably youth-dominated. This aspect of our study contributes a fresh dimension to our understanding of investor behavior in these rapidly evolving markets.

Thus, we contribute to the growing literature on behavioral aspects of cryptocurrency market participation. Our results are useful to policymakers in understanding the general crypto investor profile. Given the dominance of youth in this market, our results can help facilitate more effective regulation to curtail excessive risk-taking behaviour among youth, who may have limited loss-bearing capacity and lower capital to start with.

References


