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Insights on Crypto Investors from a German Personal Finance Management App

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Abstract: This study investigates the socio-economic characteristics, behavioral preferences, and consumption of individuals who own crypto-assets. Our empirical analysis utilizes data from a German personal finance management app where users connect their bank accounts and depots. We conducted a survey and elicited behavioral factors for financial decision-making. By combining survey with account and security account data, we identify crypto investors' preferences for financial decision-making and financial advice. Our results suggest that, in particular, students or self-employed, young, and male individuals who are risk-seeking and impatient are more likely to have invested in crypto-assets. Most crypto owners have less experience with financial advisory. They see it as too time-consuming and qualitatively poor, and instead, they prefer to decide on their own as they have self-reported high financial literacy. Investigating their consumption in more detail we conclude that crypto investors more often spend on travelling, electronics, and food delivery and less on health. Our findings suggest policymakers in identifying high-risk consumers and investors, and help financial institutions develop appropriate products.

Keywords: crypto ownership; personal finance management app; transaction data; behavioral traits; financial advice

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1. Introduction

Cryptocurrencies like Bitcoin and Ethereum have experienced an unprecedented yet volatile rise in value since 2017, gaining more and more attention in the public discourse, regulation, and investors' portfolios. The increasing public attention has been accompanied by various research streams. In particular, with their specific characteristics as digital exchange commodities, e.g., storing value in tokens, cryptocurrencies became an important topic in finance as they serve as alternative assets for portfolio diversification and hedging instrument (e.g., Bouri et al. 2017; Brière et al. 2015; Dyhrberg 2016; Subramaniam and Chakraborty 2020). Besides these works on return and portfolio allocation, there is a growing effort among scholars to understand the adoption and intention of retail investors to invest in crypto as an alternative investment, either to safeguard them and their brokers from extensive risk and financial mismanagement or to provide suitable products and marketing strategies (e.g., Coinbase 2022; Manaa et al. 2019; Mogul et al. 2020). The latter include studies that examine whether cryptocurrencies can act as a potential hedge against extreme fluctuations in investor portfolios that include MSCI constituents, regardless of market conditions. The findings suggest that cryptocurrencies have a role to play as a hedging tool, providing diversification benefits to investors looking to reduce portfolio risk (Kyriazis et al. 2023). In addition, there is emerging work on the relationship between investor sentiment and crypto investment returns and volatility (Kyriazis et al. 2022), including works on herding behaviour (Rubbaniy et al. 2022; Zhao et al. 2022) and related analyses of bubble formation (Ghosh et al. 2022). Looking at the investment landscape, Coinbase (2022) reports an average growth rate of 32% in 2022 and indicates further growth opportunities for the crypto market in the coming years. At the same time, Manaa et al. (2019) document that the largest amount of crypto-assets is held by households, which aids in our understanding of who these crypto owners actually are. This motivated household finance scholars do not only investigate the share of crypto investors, but also the socio-economic, demographic, financial, and environmental factors that influence the exposure to cryptocurrencies in individual portfolios.

Brandt Brandt (2019) employ a survey of internet users in several countries to indicate a crypto ownership share in 2019 of 4% in Germany and France, 6% in Italy, 8% in Denmark, 10% in Spain, and 20% in Turkey. Additionally, Exton and Doidge (2018) reveal shares of crypto ownership that amount to 5% in Belgium, 12% in Romania, and 18% in Turkey. A report by the Deutsche Postbank (2018) suggest a 3% share of crypto ownership among German citizens, with a 4% share among digital natives. Furthermore, Laboure and Jim (2020) conducted a survey in different countries and identified that 26% of respondents in China, 7% in Germany, Italy, and the USA, 6% in France, and 4% in the UK bought or sold cryptocurrencies in 2020. Stix (2021) investigate ownership and purchase intentions of crypto-assets using a survey among Austrian households with around 5.7% crypto owners. In particular, they are interested in crypto investors' financial capabilities and risk awareness, their trust in institutions and fiat money, and the motives driving the purchase intentions of households not yet invested in crypto-assets. Their results suggest that crypto owners are more financially knowledgeable and more risk-tolerant, while trust in institutions or fiat money does not seem to play a definitive role. Purchase intentions depend on return expectations, beliefs about the technical advantages of crypto-assets, volatility, and risk of fraud.

Based on a survey of US investors in 2018, of which more than 10% had invested in cryptocurrencies, Zhao and Zhang (2021) investigate the effects of financial literacy and investment experience on households' cryptocurrency exposure. Specifically, the results indicate that both are positively related to crypto ownership, with investment experience being the more influential factor, especially regarding previous exposure to stocks and risky assets like commodities, futures, or options. An extensive analysis is provided by Steinmetz et al. (2021) using German survey data from 2019 indicates a rate of overall crypto ownership of 9.2%. The results show that ownership is associated with young age, male gender, higher education, ideology, knowledge about crypto, and trust in the underlying technology and institutions. Moreover, they show differences in the perceived and actual usage and applications of cryptocurrencies. In a recent survey of Finnish people in 2021, Oksanen et al. (2022) investigate the relationship between cryptocurrency trading, excessive behaviors, and mental health disorders. Their results show a share of 3.6% crypto participation and that crypto exposure is influenced by male gender and younger age as well as a migration background. Additionally, crypto trading seems to be associated with behaviors such as excessive internet use, gambling, and gaming as well as mental problems like psychological distress, perceived loneliness, and stress.

Another, though smaller, part of the literature is based on data from transaction-level brokerages and security accounts, allowing gathering complementary insights into trading behavior and portfolio allocations over time. Blandin et al. (2020) use a service provider dataset to estimate around 101 million unique crypto-users in September 2020, although not considering wallets that are self-hosted. Pelster et al. (2019) exploit a UK online broker dataset to reveal that crypto trading leads to an increase in risk-seeking behavior in stock trading in terms of intensity and leverage. Relatedly, Hackethal et al. (2021) use transaction and security account data of a German online bank with about 1% of individuals depicted as crypto investors in 2017. Their findings suggest that the examined crypto investors are active traders, which are exposed to well-known investment biases, e.g., naive trend-chasing or gambling, and tend to hold rather risk-allocated portfolios. In particular, they show that risky allocations increase after an investor's adoption of cryptocurrency.

Given this background, there is various evidence of socio-economic factors such as age, gender, or education that are influential factors in determining an individual's exposure to crypto-assets. Moreover, scholars started to investigate transaction-level data and some behavioral traits like risk and trust. Nevertheless, we still see further opportunities to expand these empirical insights. On the one hand, an abundance of empirical work from the behavioral finance literature acknowledges a range of additional factors like patience (Breuer et al. 2022; Haliassos and Bertaut 1995), self-control problems (Rey-Ares et al. 2021; Sekścińska et al. 2021), loss aversion (Gomes 2005; Odean 1999), effort with financial decision making (Gambetti et al. 2022; Shapiro and Burchell 2012) and procrastination (Barboza 2018; Gamst-Klaussen et al. 2019). Thompson et al. (2021) postulate that determinants such as behavioral traits "manifest downstream in trading behavior and, eventually, in portfolio construction and investment outcomes." The latter also relates to an investor's reach for financial advice and the resulting effect on their investment choices Hackethal et al. (2021). In this light, the current literature does not fully cover all possible behavioral traits and falls short of identifying the most important and consistent traits in relation to crypto-asset investments. Relatedly, a considerable amount of research has provided data on consumption transactions as a manifestation of behavioral traits as a complementary way of capturing the influence of behavioral traits on investment decisions. Notably, because conducting surveys is associated with substantial costs, this makes analyses of behavioral influences more feasible and accessible for regulators, banks, and researchers, as consumption transactions have to be tracked since the implementation of the EU Revised Payment Service Directive (PSD2) in 2018 (European Union 2015).

Our aim in conducting this study is relate to this strand of literature and provide a more comprehensive understanding of crypto-investor behavior by incorporating a wider range of behavioral traits than previous research. In doing so, we consider all behavioral traits proposed by the behavioral finance literature in order to gain a more complete picture of investor behavior. In addition to this, we have also collected and analyzed consumption data that has not been previously explored in similar studies. Analytically, this allows us to further disentangle the specific characteristics and behaviors of crypto-investors.

For our study, we collect a unique dataset of consumption and survey data from a German financial money management app. Following the related literature, we employ both a univariate analysis and multivariate regression considering different investor groups and investigate drivers of crypto participation considering demographic factors, financial variables, behavioral traits, and consumption expenses. This analysis allows us to distangle the significant drives of crypto-ownership and investor behaviour. Likewise, we analyze which of these factors determine the intensity of crypto exposure among crypto owners. In addition, we employ an auxiliary analysis covering insights on preferences for financial advice, total portfolio size, and differences between conventional and crypto investors.

Our results show that crypto investors are mostly male, students, or self-employed, and have a high-risk appetite when it comes to financial decision-making, and exhibit some impatient tendencies. Additionally, crypto participation increases with monthly savings, suggesting that crypto investors seek new investment opportunities and diversify their total portfolio. At the same time, we do not find that crypto participation is related to age, being married or home ownership, income, or debt payments. This can be explained by the fact that our sample is based on app users that are rather young with average income, thus lacking in heterogeneity among these factors. At the intensive margin, i.e., the amount of crypto-assets held conditional on holding, we find a positive effect of age, and a negative effect of being student, homeowner, and income. Concerning behavioral traits, trust is positively related, while patience and financial effort are negatively linked to the crypto share. Additionally, we find that crypto owners compared to other individuals also exhibit a markedly distinguishable consumption profile. For example, they spend more on electronics, capital investments, food subscriptions, taxis, and train tickets, and exhibit higher credit card statements. At the same time, they spend less on pets, refueling, pharmacy, drugstore, and health insurance, and pay lower rents.[1] Last but not least, the majority of crypto investors have less experience with financial advisory, considering it to be too time-consuming and qualitatively low, and rather decide on their own as they report having enough financial literacy to do so.

Given our results, this study contributes to the literature in various ways: First, we provide new empirical insights about crypto owners related to behavioral traits and consumption patterns using a unique dataset combining both financial transaction and survey data. Second, our results specifically extend the knowledge about crypto exposure in Germany, which is still a relatively under-researched crypto investment landscape. Third, we describe the very first insight into factors that determine the intensive margin of crypto ownership, i.e., the share of crypto-assets in a user's portfolio. Finally, we point out that we observe a homogeneous group of crypto owners and show that consumption data can be used to consistently identify crypto owners beyond the usage of survey-based behavioral traits, relying on readily available PSD2 data only.

Our results also offer recommendations for policymakers, tax authorities, and financial institutions related to crypto-assets. In particular, our analysis highlights the need for appropriate regulations that address the diverse needs and behaviors of crypto investors, including taxation, anti-money laundering regulations, and investor protection measures, to mitigate risks associated with crypto ownership. Given the heterogeneity revealed in our analysis, targeted measures should be taken to prevent tax evasion by certain groups of crypto investors, including providing education and resources, offering risk-management tools, and developing new investment products catering to different risk profiles and investment goals.

This study is structured as follows. In the next section we describe the financial transaction and survey data used and afterward we describe the behavioral traits with a brief literature review behind them. Next, we conduct univariate analyses of differences between crypto, conventional, and non-investors with respect to their characteristics, behavioral traits, and consumption data. Further, using multivariate regressions, we identify the determinants of crypto participation and provide additional insights on preferences for financial advice, portfolio size, and differences between investor types. Lastly, we discuss and conclude our results.

2. Data

We cooperate with a German company that provides a personal finance management app. With this app, users can connect all their bank and security accounts in one place and, thus, can get a holistic overview of all their expenditures, savings, investments, and debts.

We invited about 56,000 pre-selected active customers[2] to a 4–5 min survey in the app and incentivized them for participation with a EUR 20 voucher for Amazon.de.[3] We conducted the survey from August to September 2020. After filtering invalid responses, and transaction data since 2015 due to lack of data availability, we end up with a net sample size of 1533. As we can see in Figure 1, among these 1533 we observe 689 individuals who hold any kind of securities. Overall, we identified 75 crypto owners that amount to around 5% crypto ownership share in our sample.

We received data on demographics such as age, gender, employment, or education status, and for the period of March 2015 to November 2021 all available bank account transactions and monthly security account holdings (see Table 1). To increase sample sizes and ultimately estimation power, we imputed some demographic variables that were missing on average in 28.3% of the sample.[4] The bank account transactions are provided on transaction level and contain information on transaction receiver, timestamp, and a label, e.g., income, restaurant, saving, children, cinema, or online shopping.[5] The total monthly amount of security account holdings is the sum of all security account holdings that is available to the user connected to the app at the end of a month. Due to the lack of data availability, we only focused on the time period between January 2018 and November 2021.

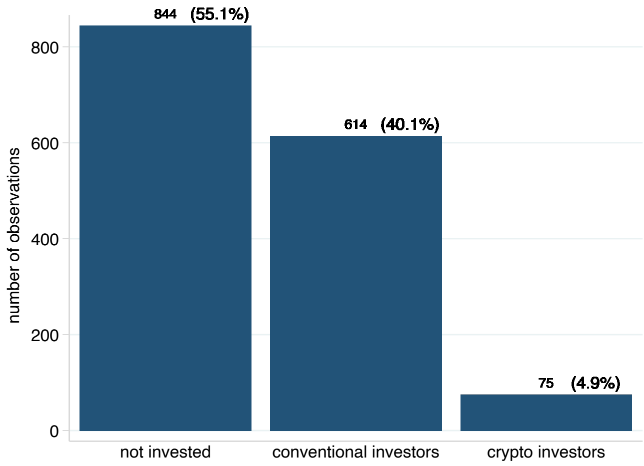

Figure 1. Number of cases of non-invested individuals, individuals invested in conventional assets, in cryptocurrencies. **Source:** Own data.

Table 1. Different data sources received from the cooperating company. **Source:** Own data.

	Data Sources	Variables
1	Survey	Behavioral traits
2	Demographics	Age, gender, employment, and living status
3	Account transactions	Labeled transactions
4	Security accounts	Monthly security balances, crypto wallets

2.1. Identification of Crypto Owners

When analyzing crypto investors, the big challenge is to actually identify individuals owning crypto-assets because crypto wallets are usually stored outside the scope of financial institutions and are thus hard to track. We identified crypto owners through the crypto wallet users which were connected to the app. Since November 2021, it was possible to connect the most common crypto wallets. Since the app encourages its users to connect all their available accounts and wallets in order to archive a holistic overview of all finances, we believe that our data provide good coverage of all available accounts and wallets.

From the cooperating company, we received all available historic data on monthly security account balances. Furthermore, the company provided an indicator that shows which security account is (a) a conventional security account that includes assets such as stocks, ETFs, bonds, etc., or (b) a crypto wallet that contains typical crypto-assets such as Bitcoins, Ether, and others. although we only received monthly account balances and do observe any assets held, we still indentify which user is a crypto owner. The remaining group, (c) non-invested, are individuals for who we do not observe any security account or crypto wallet.

In contrast to other studies that either rely on self-reported information of survey participants on crypto ownership and their wallets (e.g., Bonaparte 2022; Fujiki 2020; Steinmetz et al. 2021), or studies that only observe indirect cryptocurrency investments from crypto holders based on data of only one bank (e.g., Hackethal et al. 2021), we instead potentially observe all crypto wallets of the app users. Crypto wallets we observe are Coinbase (152 wallets), Bitpanda (27 wallets), Binance (5 wallets), Kraken (3 wallets), and others (26 wallets).[6] To the best of our knowledge, our study is the first that uses data from different kinds of crypto providers.

We observe that crypto investors hold on average 6.4 security accounts[7] with an average total portfolio balance of EUR 23,787. They hold EUR 3573 in crypto wallets[8] and EUR 20,214 in conventional securities.

2.2. Behavioral Traits

In this section, we present the self-assessed behavioral traits and provide a brief theoretical background on each. We elicit the following behavioral traits using an item battery listing statements to which respondents could agree or disagree on a 7-point Likert scale. In accordance with the cooperating company, we agreed on nine survey questions that cover risk, trust, patience, self-control problems, loss aversion, financial effort and procrastination. The survey questions are presented in Table 2. For eased interpretation, we standardize each of the traits in such a way that they exhibit a mean zero and a standard deviation of one. We elicit the following behavioral traits which prior research has identified as being relevant for financial decision-making and investment behavior.

Table 2. Survey questions on behavioral traits. **Source:** Own survey.

	Behavioral Trait	**Survey Question**
1	risk	If you personally make savings or investment decisions, how would you describe your risk attitude?
2	trust	What is your opinion on the following statement? In general, people can be trusted.
3	patience	I would rather spend money when it is there than put it aside.
4	patience	I am willing to give up something today in order to benefit more in the future.
5	self-control bias	I have created a long-term financial plan for myself (and my family).
6	self-control bias	It often happens that I spend money on things that, in hindsight, I would have preferred not to have bought.
7	self-control bias	I regularly cancel my subscriptions and contracts to get better conditions.
8	procrastination	I tend to put off important financial decisions.
9	effort	I find it very exhausting to make financial decisions.
10	loss aversion	The possibility of even small losses on my savings makes me nervous.
11	loss aversion	When making financial decisions, I am afraid of making mistakes that I regret afterwards

Note: Here, we list the behavioral trait with the underlying survey questions that we translated from German to English. The original survey questions in German are listed in Table A5.

1. *Risk preference*: We elicit respondents' risk-seeking preference with the survey question *"If you personally make savings or investment decisions, how would you describe your risk attitude?"*. Dohmen et al. (2011) show that the willingness to take risks determines whether an individual is invested in stocks. Steinmetz (2021) document results from several studies and summarizes that cryptocurrencies are perceived to be high-risk assets and studies such as Bonaparte (2022), Bonaparte (2021), Fujiki (2021), and Stix (2021) show that investors with greater risk levels tend to have invested in crypto-assets. Therefore, we expect that crypto investors in our dataset are high-risk-seekers.

2. *Trust*: Further, we asked respondents' trust preference by posing the question *"What is your opinion on the following statement? In general, people can be trusted."*

As pointed out by Steinmetz et al. (2021), trust itself is an important driver of investment decisions in cryptocurrencies. However, the literature understands trust differently, for example, trust as a money transfer (Böyükaslan and Ecer 2021), trust in Blockchain technology behind cryptocurrency (Krombholz et al. 2017), or trust towards financial institutions (Guiso et al. 2008; Stix 2021). Thus, these studies make it difficult to grasp a consistent understanding of trust. In contrast, we focus on *general trust* that is not yet covered by the literature. Furthermore, studies such as Falk et al. (2018) describe that trust is related to risk and, e.g., Olsen (2012), outlines that there is a remarkable "trust-risk conjunction" in financial decision-making. Therefore, we expect it to be related to crypto investors' behavior.

3. Patience: To elicit the degree of individual patience we use two items: "*I would rather spend money when it is there than put it aside*" and "*I am willing to give up something today in order to benefit more in the future.*"

Both responses are based on Breuer et al. (2022) and Haliassos and Bertaut (1995) who use similar response options on self-assessed patience. Patience as a behavioral trait represents an important determinant for investment decisions as it is tightly connected to investment performance and overtrading. Impatient investors tend to have a short time horizon; they trade excessively and might result in lower returns (Aksoy and Saglam 2006; Gur 2022; Odean 1999). Therefore, we expect that crypto investors exhibit greater levels of impatience as they invest in risky crypto-assets from which they expect large returns in the short term.

4. Self-control problems: Next, we surveyed self-control problems (hereafter only *self-control*) with the three response options: "*It often happens that I spend money on things that, in hindsight, I would have preferred not to have bought*", "*I regularly cancel my subscriptions and contracts to get better conditions*" and "*I have created a long-term financial plan for myself (and my family).*" These responses are comparable to Rey-Ares et al. (2021). The authors relate self-control to financial decision-making and find that self-control problems, especially among Millennials, might result in bad financial decisions. Sekścińska et al. (2021) find that self-control is positively associated with the propensity of being invested, but negatively with the propensity to take investment risks. Thus, we expect that crypto owners tend to show higher levels of self-control problems.

6. Loss aversion: Loss aversion was elicited by the response options: "*The possibility of even small losses on my savings makes me nervous*" and "*When making financial decisions, I am afraid of making mistakes that I regret afterward.*" Loss aversion specifies that investors tend to weight losses more severely compared to winnings of the same amount, i.e., they are more sensitive towards losses (Gomes 2005). This also implies that investors wish to avoid losses and ultimately regret them (Odean 1999). Most crypto investors are more risk-seeking and have already experienced losses in crypto-assets (Krombholz et al. 2017) and as less loss aversion is associated with a higher probability of stock market participation (Dimmock and Kouwenberg 2010), we, therefore, expect that crypto owners are less loss averse compared to conventional investors.

7. Financial effort: Next, we survey the degree of effort with financial decision-making (hereafter only *effort*) by the question: "*I find it very exhausting to make financial decisions.*" Effort has been related to financial decision-making by several studies (Bernaola et al. 2021; French et al. 2021; Gambetti and Giusberti 2012; Gambetti et al. 2022; Shapiro and Burchell 2012).[9] Our survey question on effort is closest related to Shapiro and Burchell (2012) who identified financial effort as a relevant determinant of financial decision-making. Gambetti et al. (2022) showed that effort is positively related to opt-out investment decisions, but not to opt-in decisions. In other words, investors tend to make financial decisions effortlessly. Furthermore, Oksanen et al. (2022) found that lower levels of effort, described in terms of psychological distress, perceived loneliness, and stress are positively related to crypto ownership. Based on this, we expect that crypto owners tend to have low levels of behavioral trait effort.

8. Procrastination: Lastly, we elicited procrastination with the item "*I tend to put off important financial decisions.*" With this trait, we intend to cover individuals' laziness when they have to decide on their finances. Procrastination is a significant predictor in financial planning and is highly related to impulsiveness, impulsivity, impatience, and present-bias preferences (Barboza 2018; Gamst-Klaussen et al. 2019). Consequences of this trait are unhealthy financial planning such as "postponing retirement savings, last minute shopping, and not paying bills on time" (Gamst-Klaussen et al. 2019). As procrastinating individuals tend to act less impulsively, we expect that crypto investors do not exhibit such behavior.

3. Who Are the Cryptocurrency Owners?

3.1. Univariate Analysis of Crypto Investors' Characteristics, Behavioral Traits, and Consumption

In this section, we seek to answer the question of who the crypto owners are. We start with a univariate analysis using descriptive statistics and sample *t*-tests to compare the three groups in our sample: (1) crypto investors, (2) conventional investors, and (3) non-invested. Next, we build up on these univariate insights to estimate a set of regression models to identify and consolidate the most important of these factors in determining crypto exposure. In doing so, we do not only analyze the choice to invest in crypto-assets but also the intensity, i.e., the share of crypto-assets in a user's portfolio. To the best of our knowledge, the latter has not yet been investigated in the adjacent literature.

To begin with, we compare demographic characteristics, financial variables, and behavioral traits across the three groups, investigating their means, absolute differences, and significance levels based on a two-sided *t*-test of mean comparison. The results are shown in Table 3, starting with a comparison of the statistics of crypto and conventional investors (column (1) vs. (2)).

Table 3. Means and *t*-tests of crypto owners, conventional and non-investors of characteristics and behavioral traits. **Source:** Own data.

	(1) Crypto Investors	(2) Conventional Investors	(3) Non-Invested	(1)–(2) Diff. Crypto and Conventional Investors	(1)–(3) Diff. Crypto and and Non-Invested	(2)–(3) Diff. Conventional and Non-Invested
Characteristics						
Age	33.39	35.17	34.53	−1.78	−1.14	0.64
Male	0.88	0.73	0.50	0.15 **	0.38 ***	0.23 ***
Retired	0.20	0.24	0.34	−0.04	−0.14 **	−0.10 ***
Married	0.64	0.62	0.57	0.02	0.07	0.05 **
Student	0.45	0.31	0.21	0.14 **	0.24 ***	0.10 ***
Self-employed	0.27	0.17	0.06	0.10 **	0.21 ***	0.11 ***
Monthly transactions	49.24	52.35	53.61	−3.11	−4.37	−1.26
# All security accounts	6.43	1.78		4.64 ***		
# Non-crypto security accounts	2.32	1.78		0.54 ***		
Total portfolio balance	23,787.21	30,964.29		−7177.08		
Behavioral traits						
Risk	4.88	4.41	3.42	0.47 ***	1.46 ***	0.99 ***
Trust	4.04	4.03	3.88	0.01	0.16	0.15 **
Patience	2.59	2.88	3.32	−0.29 *	−0.73 ***	−0.44 ***
Self-control	4.82	4.68	4.06	0.14	0.75 ***	0.61 ***
Procrastination	2.67	2.93	3.33	−0.26	−0.67 ***	−0.4 ***
Effort	2.85	3.31	3.95	−0.45 **	−1.09 ***	−0.64 ***
Loss aversion	2.79	3.07	4.00	−0.27	−1.21 ***	−0.94 ***
n	75	614	844			

Note: In the first three columns we present means of different characteristics and behavioral traits conditional on the three groups (1) crypto, (2) conventional investors, and (3) non-invested. In the last three columns, we show absolute differences of the means with significance levels 10%, 5%, and 1% indicated by *, **, *** of a two-sided *t*-test. Note that the age variable and the married and employed dummies are imputed, and these are missing on average 28.3% in the sample.

We see that crypto owners are significantly more often of male gender. 88% of crypto owners are male but only 73% conventional investors are male. Additionally, crypto investors are more often students (45% vs. 31%) or self-employed (27% vs. 17%).

Looking at the behavioral traits, we observe that crypto owners exhibit significantly different levels of risk, patience, and effort. The average level of risk of crypto investors is 4.88 and significantly higher compared to the mean of conventional investors which is 4.41. The mean of effort of crypto investors lies at 2.85 and is lower compared to the mean of 3.31 of conventional investors.

Comparing the means between crypto investors and non-investors, we observe again that crypo investors are significantly more often male (88% vs. 50%), students (45% vs. 31%), and self-employed (27% vs. 6%), but less frequently retired (20% vs. 34%). Also, we observe significant differences in terms of behavioral traits. In particular, crypto investors exhibit higher levels of risk (4.88 vs. 3.42), but lower levels of patience (2.59 vs. 3.32), self-control (4.82 vs. 4.06), procrastination (2.67 vs. 3.33), effort (2.85 vs. 3.95), and loss-aversion (2.79 vs. 4.00). Notably, trust is the only behavioral trait for which we do not find any significant differences for all group comparisons.

Table 4 shows the means of the three groups for different consumption categories. Starting with the main consumption categories, we observe that crypto investors, compared to conventional investors, tend to earn significantly less than conventional investors (EUR 2249.53 vs. EUR 2699.49). Additionally, crypto investors tend to spend less on health care (EUR 58.88 vs. EUR 77.75), pets (EUR 9.49 vs. EUR 18.59), refueling (EUR 60.07 vs. EUR 76.82), insurance (EUR 171.81 vs. EUR 256.80), and have less living expenses (EUR 531.97 vs. EUR 669.90). In the lower pane of Table 4 we show the conditional means of consumption subcategories we selected based on their significance level. In comparison to conventional investors, crypto investors exhibit lower expenses for electronics, but fewer expenses for pets (EUR 6.53 vs. EUR 18.02), refueling (EUR 60.07 vs. EUR 87.18), pharmacy (EUR 26.91 vs. EUR 35.10), health insurance (EUR 30.55 vs. EUR 82.34), or restaurants (EUR 34.91 vs. EUR 41.07).

Comparing the means between crypto investors and non-invested individuals, we see more pronounced differences. Crypto investors withdraw less cash (EUR 254.72 vs. EUR 326.03), spend less on leisure (EUR 76.20 vs. EUR 91.35), pets (EUR 9.49 vs. EUR 26.06), and food (EUR 183.33 vs. EUR 230.11), but save more (EUR 666.99 vs. EUR 274.99). Likewise, the differences are also remarkable among the subcategories. Crypto investors exhibit higher expenses for electronics (EUR 212.41 vs. EUR 155.67), capital investments (EUR 648.89 vs. EUR 111.63), train tickets (EUR 38.70 vs. EUR 26.31), credit card statements (EUR 258.31 vs. EUR 175.84) or for food subscriptions (EUR 16.14 vs. EUR 10.29). On the other hand, they spend less on pets (EUR 6.53 vs. EUR 18.02), refueling (EUR 60.07 vs. EUR 87.18), pharmacy (EUR 22.46 vs. EUR 30.63), or in drugstores (EUR 26.91 vs. EUR 42.71).

Table 4. Monthly means of consumption categories and *t*-tests of crypto owners, conventional and non-investors. **Source:** Own data.

	(1) Crypto Investors	**(2) Conventional Investors**	**(3) Non-Invested**	**(1)–(2) Diff. Crypto and Conventional Investors**	**(1)–(3) Diff. Crypto and and Non-Invested**	**(2)–(3) Diff. Conventional and Non-Invested**
Main Consumption Categories						
income	2249.53	2699.49	2309.92	−449.96 *	−60.39	389.57 ***
Cash withdrawals	254.72	304.53	326.03	−49.81	−71.31 **	−21.50
Vocational training	48.94	52.14	48.35	−3.20	0.58	3.79
Financial expenses	627.21	761.93	548.15	−134.73	79.06	213.79 ***
Financial receipts	81.91	91.70	87.45	−9.79	−5.54	4.25
Leisure expenses	76.20	86.71	91.35	−10.51	−15.15 *	−4.63
Health care expenses	58.88	77.75	69.50	−18.87 *	−10.62	8.25 **
Pet expenses	9.49	18.59	26.06	−9.10 **	−16.57 ***	−7.48 ***
Children expenses	41.87	60.49	64.78	−18.62	−22.91	−4.29
Food expenses	183.33	215.28	230.11	−31.95	−46.78 **	−14.83
Holiday expenses	258.23	285.83	252.40	−27.59	5.84	33.43 **
Shopping expenses	306.28	291.83	309.51	14.45	−3.23	−17.68 *
Savings expenses	666.99	536.43	274.99	130.55	392.00 ***	261.44 ***
Mobility expenses	98.89	108.69	106.06	−9.80	−7.17	2.63
Insurance expenses	171.81	256.80	205.66	−84.99 **	−33.85	51.14 ***
Living expenses	531.97	669.90	566.44	−137.93 **	−34.47	103.46 ***
Other expenses	1922.64	2291.23	1391.32	−368.59	531.32 **	899.91 ***
Other receipts	2498.57	3038.71	1839.40	−540.15	659.16 ***	1199.31 ***
Debt	−689.24	−437.63	−300.58	−251.61	−388.65	−137.04

Table 4. *Cont.*

	(1) Crypto Investors	(2) Conventional Investors	(3) Non-Invested	(1)–(2) Diff. Crypto and Conventional Investors	(1)–(3) Diff. Crypto and and Non-Invested	(2)–(3) Diff. Conventional and Non-Invested
Selected Consumption Subcategories						
Pet	6.53	12.50	18.02	−5.97 **	−11.48 ***	−5.52 ***
Refueling	60.07	76.82	87.18	−16.75 **	−27.11 ***	−10.36 ***
Pharmacy	22.46	31.68	30.63	−9.22 **	−8.16 ***	1.05
Drugstore	26.91	35.10	42.71	−8.19 **	−15.81 ***	−7.62 ***
Health insurance	30.55	82.34	47.91	−51.79 **	−17.36	34.43 ***
Restaurant	34.91	41.07	37.41	−6.16 *	−2.50	3.66 ***
Electronics	212.41	170.09	155.67	42.32 *	56.74 ***	14.42
Interest	9.08	15.80	15.54	−6.72 *	−6.46 *	0.26
Rent	377.13	478.39	399.91	−101.26 *	−22.78	78.48 ***
Furniture	123.07	160.36	134.75	−37.28 *	−11.67	25.61 ***
Capital investment	648.89	410.27	111.63	238.62	537.26 ***	298.64 ***
Train ticket	38.70	35.42	26.31	3.28	12.39 ***	9.11 ***
Credit card statement	258.31	264.93	175.84	−6.62	82.47 **	89.08 ***
Food subscriptions	16.14	11.09	10.29	5.05	5.85 **	0.80
Taxi	5.68	5.94	3.73	−0.26	1.95 *	2.21 ***
n	75	550	843			

Note: In the first three columns, we present conditional means of different main consumption categories and of selected subcategories of the three groups: (1) crypto, (2) conventional investors, and (3) non-invested. Due to the large amount of subcategories, we only show those with significantly different means. In the last three columns, we show absolute differences of the means with significance levels 10%, 5%, and 1% indicated by *, **, *** of a two-sided *t*-test. According to the cooperating company, not all transactions are perfectly identified and mapped to one of the consumption categories listed in Table A12. Remaining unlabeled transactions fall into "other expenses", which results in high values. We calculated the means by aggregating all transactions in one category and month, and then calculating the mean across all observed months. Robust standard errors are in parentheses. ***, **, and * indicate coefficients that are significant at the 1, 5, and 10% levels, respectively.

Overall, crypto investors indeed show significantly different socio-economic and financial characteristics, behavioral traits, and consumption patterns. Based on these initial findings, we continue with a regression analysis to investigate which of these factors determine crypto ownership in a multivariate setting.

3.2. Identifying the Determinants of Crypto Ownership

To make full use of our comprehensive dataset, we conduct two regression model specifications. Herewith, we do not only identify crypto ownership determinants but also investigate their influence at the intensive margin, i.e., the total portfolio size and the crypto share of the total portfolio.

To investigate the factors that determine a user's crypto ownership, our first regression specification is based on the following probit model:

$$CryptoOwnership_i = Probit(\beta_0 + \gamma X_i + \epsilon_i) \tag{1}$$

where X_i is a vector containing our behavioral traits, demographics, financial variables, and consumption variables. Notably, we include all behavioral traits, financial and demographic variables from our previous analysis, while the consumption variables are selected via backward selection to keep the model parsimonious. In particular, we only focus on the consumption subcategories previously listed in Table 4, as the main categories are artificially created by the data provider and do not necessarily pool the subcategories in an economically meaningful way. To identify the determinants across all user groups, we regress a dummy that indicates 1 if the individual is invested in crypto-assets, and 0 if not, using our whole sample.

We start our regression analysis by estimating the first specification of the whole sample. The results are presented in Table 5. Starting with the demographic factors, we see that only gender is highly significant throughout all columns, indicating a higher probability of crypto exposure if the user is male. Furthermore, the coefficient for retired is weakly significant across all columns, indicating that a retired person is less likely to own crypto. Meanwhile, the coefficients for student and self-employed have both positive effects, although they are not always significant and seem to lose effect once the behavioral traits or consumption variables are added to the model. From the financial variables, the savings variable is positively significant but vanishes once we control the behavioral traits. Among the behavioral traits, we see that only risk exhibits a significantly positive coefficient which is robust across the different models. Patience has a significantly negative effect, but only in the fourth column. The remaining behavioral traits turn out to be insignificant. From our large set of consumption variables, our backward selection procedure demonstrates that expenses on interest payments are significantly negative, while payments for food subscriptions have a significantly positive effect.

Table 5. Probit regression of crypto participation. **Source:** Own data.

	Crypto Participation					
	(1) **Probit**	**(2)** **Probit**	**(3)** **Probit**	**(4)** **Probit**	**(5)** **Probit**	**(6)** **Probit**
male	0.572 ***	0.558 ***	0.370 **		0.589 ***	0.411 ***
	(0.141)	(0.142)	(0.155)		(0.146)	(0.158)
age	−0.004	−0.001	0.0002		0.002	0.003
	(0.006)	(0.006)	(0.006)		(0.007)	(0.007)
married	0.032	0.037	0.020		0.031	0.013
	(0.117)	(0.117)	(0.118)		(0.117)	(0.117)
student	0.289 **	0.244 *	0.190		0.236 *	0.176
	(0.123)	(0.133)	(0.136)		(0.135)	(0.137)
retired	−0.239 *	−0.268 *	−0.249 *		−0.286 **	−0.260 *
	(0.135)	(0.138)	(0.138)		(0.139)	(0.140)
self-employed	0.435 ***	0.317 *	0.297 *		0.281	0.250
	(0.147)	(0.172)	(0.179)		(0.172)	(0.179)
homeowner	−0.369	−0.419	−0.382		−0.423	−0.380
	(0.341)	(0.353)	(0.356)		(0.362)	(0.365)
log(income)		−0.045	−0.040		−0.039	−0.041
		(0.031)	(0.032)		(0.033)	(0.034)
log(saving)		0.048 **	0.034		0.048 **	0.033
		(0.023)	(0.023)		(0.023)	(0.023)
log(total debt)		−0.044	−0.044		−0.039	−0.040
		(0.028)	(0.027)		(0.028)	(0.028)
risk			0.214 ***	0.277 ***		0.223 ***
			(0.075)	(0.075)		(0.076)
trust			−0.003	0.008		−0.003
			(0.057)	(0.055)		(0.058)
patience			−0.109	−0.138 *		−0.116
			(0.076)	(0.074)		(0.076)
self-control			0.060	0.063		0.056
			(0.140)	(0.132)		(0.143)
loss aversion			−0.018	−0.057		−0.023
			(0.087)	(0.083)		(0.089)
procrastination			−0.033	−0.007		−0.049
			(0.079)	(0.075)		(0.082)
effort			−0.044	−0.060		−0.045
			(0.073)	(0.071)		(0.075)
log(interest)					−0.094 *	−0.086 *
					(0.052)	(0.052)

Table 5. *Cont.*

	Crypto Participation					
	(1) **Probit**	**(2)** **Probit**	**(3)** **Probit**	**(4)** **Probit**	**(5)** **Probit**	**(6)** **Probit**
log(food subscriptions)					0.072 **	0.095 ***
					(0.035)	(0.037)
Constant	−2.060 ***	−1.879 ***	−1.848 ***	−1.789 ***	−1.941 ***	−1.914 ***
	(0.273)	(0.359)	(0.364)	(0.0656)	(0.373)	(0.380)
Observations	1533	1533	1532	1532	1533	1532
Pseudo R^2	0.076	0.089	0.127	0.076	0.102	0.142

Note: Here, we regress a dummy that is one if the respondent owns crypto assets, else zero. The behavioral traits, risk, trust, patience, and procrastination are standardized with mean zero and standard deviation one. Since self-control and loss aversion are based on multiple questions, we retrieved factors from both by applying factor analysis. Income, savings, and debt are monthly averages. Robust standard errors are in parentheses. ***, **, and * indicate coefficients that are significant at the 1, 5, and 10% levels, respectively.

3.3. Investigating How Crypto Investors Allocate Their Portfolios

Our second regression specification focuses on the intensive margin and investigates which of the determinant factors affect the portfolio share of crypto-assets conditional on holding crypto-assets. We estimate this by the following OLS model:

$$\{log(CryptoShare_i) = \beta_0 + \beta X_i + \epsilon_i \mid CryptoOwnership_i = 1\} \quad (2)$$

Again, we select the consumption variables via backward selection. The results are listed in Table 6. Keeping the rather small sample size in mind, our results suggest a significantly negative effect of the coefficient for homeowners that is robust across all models. Likewise, the student and retired coefficients are negative. Concerning financial variables, income has a highly significant negative coefficient, while savings and debt exhibit no significant effects. Notably, the other demographic factors loose significance compared to our first specification, which can be explained by the rather homogeneous sample of crypto investors. From our behavioral traits, trust has a weakly significant negative effect, while both patience and effort have a positive effect. Patience seems to be the most robust of these traits. Lastly, the significantly positive drugstore expenses are the only consumption variable left over from the backward selection.

Table 6. OLS regression of crypto share in users' portfolio. **Source:** Own data.

	Crypto Share, Conditional on Crypto Ownership					
	(1) **OLS**	**(2)** **OLS**	**(3)** **OLS**	**(4)** **OLS**	**(5)** **OLS**	**(6)** **OLS**
male	−6.736	−4.690		0.063	−3.090	−0.157
	(13.430)	(13.790)		(13.380)	(13.270)	(12.770)
age	0.274	0.420		1.083 *	0.0003	0.733
	(0.576)	(0.608)		(0.605)	(0.601)	(0.625)
married	−7.197	−5.067		−11.030	−7.734	−12.440
	(9.800)	(10.110)		(9.889)	(9.848)	(9.897)
student	−10.830	−13.670		−20.410 **	−12.170	−18.230 **
	(9.783)	(9.948)		(9.640)	(9.339)	(9.018)
retired	−5.803	−8.298		−26.740 **	−12.220	−27.370 **
	(11.940)	(12.580)		(12.780)	(11.980)	(12.010)
self-employed	9.052	−4.251		−4.888	−8.728	−8.637
	(11.760)	(15.900)		(10.600)	(13.420)	(9.884)
homeowner	−24.040 *	−25.500 *		−56.750 ***	−26.790 **	−53.850 ***
	(12.660)	(13.200)		(15.340)	(12.490)	(14.880)
log(income)		−2.639		−4.644 **	−9.894 ***	−9.705 ***
		(2.433)		(1.957)	(2.960)	(2.646)

Table 6. *Cont.*

Crypto Share, Conditional on Crypto Ownership						
	(1) **OLS**	**(2)** **OLS**	**(3)** **OLS**	**(4)** **OLS**	**(5)** **OLS**	**(6)** **OLS**
log(saving)		−0.219		1.414	0.940	1.932
		(1.784)		(1.927)	(1.726)	(1.874)
log(debt)		−0.752		−1.057	−1.280	−1.443
		(2.139)		(2.301)	(2.026)	(2.204)
risk			0.046	2.914		3.836
			(7.049)	(7.118)		(6.810)
trust			−3.469	−8.341 *		−7.272
			(4.637)	(4.299)		(4.360)
patience			5.244	9.227 *		8.136 *
			(4.697)	(4.930)		(4.789)
self-control			−7.890	−0.005		−1.859
			(9.664)	(11.400)		(10.730)
loss aversion			1.233	12.100		12.810
			(10.720)	(11.470)		(10.780)
procrastination			−6.293	−6.732		−6.337
			(5.736)	(5.886)		(5.539)
effort			12.480	16.440 *		12.660
			(8.550)	(8.677)		(8.136)
log(drugstore)					15.930 ***	11.600 ***
					(4.340)	(4.337)
Constant	38.110 *	53.130 **	40.920 ***	58.450 ***	71.000 ***	70.490 ***
	(21.790)	(24.910)	(5.791)	(20.660)	(24.730)	(21.680)
Observations	74	74	74	74	74	74
R-squared	0.049	0.069	0.136	0.314	0.194	0.373

Note: Here, we regress the share of crypto assets held in the portfolio. The behavioral traits, risk, trust, patience, and procrastination are standardized with mean zero and standard deviation one. Since self-control and loss aversion are based on multiple questions, we retrieved factors from both by applying factor analysis. Income, savings, and debt are monthly averages. Here, we estimate following model: $\{CryptoShare_i = \beta_0 + \beta X_i + \epsilon_i \mid CryptoOwnership_i = 1\}$ with $CryptoShare_i$ as the percentage share of crypto assets in the portfolio of user i. Robust standard errors are in parentheses. ***, **, and * indicate coefficients that are significant at the 1, 5, and 10% levels, respectively.

3.4. Additional Insights on Financial Advice, Portfolio Size, and Differences to Conventional Investors

In this section, we employ additional analyses where we cover insights on financial advice, total portfolio size, and differences between conventional and crypto investors.

3.4.1. Crypto Owners Preferences for Financial Advice

In our survey, we asked respondents about their past experience with financial advice in general. We first asked whether they have ever consulted a financial advisor or not. Among the advised individuals, we further asked for which specific products they requested advice about, and how satisfied they were. In addition, we asked respondents for their specific reasons why they never consulted a financial advisor. In the appendix, we provide Table A7 which compares the average responses of the three samples: (a) crypto investors, (b) conventional investors, and (c) non-invested individuals.

Overall, 43% of the crypto investors in our sample have experience with financial advice. This number is 10 percentage points lower than conventional investors (53%), but 2 percentage points more than non-invested users (45%). On average, all three groups were similarly satisfied with their experience (about 4.39 to 4.80, on a 7-point Likert scale). Among the crypto owners who ever consulted a financial advisor, mostly asked for advice for investments (69%), insurance (66%), and for pension products (50%). Loans and savings products (19 and 13%) are at the bottom of the requested advice. Interestingly, more than half of those who have never asked for financial advice state that they have enough financial literacy (51%) and that they do not trust advisors sufficiently (42%).

Additionally, 35% of crypto owners state that financial advice is too time-consuming which is statistically significantly different from conventional investors (13%). Lastly, a smaller but still statistically significant amount of crypto investors (30%) report that financial advisors lack quality, compared to only 18% of conventional investors.

Comparing the responses of crypto owners to non-invested individuals, we observe that crypto owners request advice on savings and pension products less frequently, but much more often for investment products (crypto investors: 13% on savings, 50% on products and 69% investments; non-investers: 45% on savings, 65% on pension and 49% on investment products). Additionally, among the sample of non-advised respondents, crypto owners and non-investers differ substantially in the reasons 'no money' (16% crypto investors vs. 47% non-invested), 'low quality' (30% vs. 10%), 'time-consuming' (35% vs. 17%), and 'enough financial literacy' (51% vs. 16%). We do not observe significant differences among the three samples for advised real estate products. Also the same fractions of the three samples who never asked for advice stated that it is 'too expensive' (23 to 26%), that they lack trust (30 to 42%), and that they would rather receive advice from their peers (14 to 17%).

To sum up, crypto investors overall ask for financial advice less frequently. Among all surveyed crypto investors, only 43% stated that they ever consulted a financial advisor and stated that they asked for advice on investment, insurance, and pension products. Additionally, those who responded that they never consulted a financial advisor stated that they have 'enough financial literacy' and that financial advice is too 'time-consuming'. Notably, these results are similar to Zhao and Zhang (2021).

Our findings from the survey are in line with the literature that also finds that crypto owners are so-called 'do-it-yourself (DIY) investors' (Hackethal et al. 2021). The authors find that such investors log in to their online banking to check their financial performance more frequently than other investors, and even see investment as entertainment. Putting this into context, this observation matches our findings that crypto investors state that they have enough financial literacy, see financial advice as too time-consuming, and therefore prefer to conduct investment decisions on their own.

To further investigate this insight into DIY-crypto investors, we set up a regression specification to identify the effect of crypto ownership on the probability of seeking financial advice. For this, we estimate the following probit model:

$$FinancialAdvice_i = Probit(\beta_0 + hasCrypto_i + \gamma X_i + \epsilon_i) \tag{3}$$

with $FinancialAdvice_i$=1 if the respondent i answered the question 'Have you ever sought financial advice?' with 'yes', and 0 with 'no'. X_i is a vector of controls that include characteristics, behavioral traits, and income, savings or debt of i, and $hasCrypto_i$ is a dummy that indicates a 1 if the respondent holds crypto-assets.

We show the results in Table A8 in the Appendix B. Overall, we see a negative coefficient of crypto ownership, which means that crypto ownership might be reversibly related to seeking financial advice. The marginal effect of $hasCrypto_i$ for example in column (1) is -0.044. This means that the probability that the respondent has asked for financial decreases by 4.4 percentage points if he owns crypto-assets. In other words, as DIY investors, they manage their investment decisions on their own instead of consulting an advisor. This can be related to (Bonaparte 2022), who argues that crypto owners are rather sophisticated investors with high financial literacy. However, the resulting effect of crypto ownership on seeking financial advice is not significant and has to be interpreted with caution.

3.4.2. How Do Crypto Investors Differ From Conventional Investors?

For additional insights, we now repeat both regression specifications from our previous sections for a subsample to compare the differences between crypto and conventional investors. We estimate the following probit model, conditional on being invested:

$$\{CryptoParticipation_i = \beta_0 + \beta X_i + \epsilon_i \mid beingInvested_i = 1\} \tag{4}$$

where $beingInvested_i$ specifies the subsample of all conventional and crypto investors. With this specification, we seek to identify on the basis of conventional investors and identify the factors that determine crypto ownership, specifically among invested users only. The results of the model are displayed in Table A9. Overall, we observe that the characteristics of being male and having high risk appetite determine crypto ownership. Further, we see that being a homeowner and the height of paid rent significantly reduce crypto participation. No other covariate exhibits a significant coefficient and, thus, appears to be crypto ownership-determining.

We further add to these insights with our next specification, which investigates drivers of total portfolio size among crypto and conventional investors. This is estimated by an OLS model on portfolio size in logs conditional on being an investor. Thereby, we analyze whether the total portfolio size is higher if the investor owns crypto-assets.

$$\{log(PortfolioSize_i) = \beta_0 + hasCrypto_i + \beta X_i + \epsilon_i \mid Invested_i = 1\} \tag{5}$$

We observe that owning crypto-assets increases total portfolio size. Investors are interested in extending their investment opportunities by diversification where they include crypto-assets in their portfolio. This is visible by the positive and significant coefficients of age and income which both indicate that older and high-income investors exhibit higher portfolios. Furthermore, the behavioral traits risk, patience, self-control, and loss-aversion show significant results. Investors who are risk-seeking, impatient, but self-controlled, show low levels of loss-aversion and tend to increase their portfolio. At the same time, none of the remaining demographic variables appear to be significant.

4. Discussion

In this section, we discuss our results and put them in the context of the corresponding literature. Furthermore, we critically reflect on our analysis considering the dataset used, the conducted survey, and the investigated behavioral traits.

For the most part, we find comparable results that are in line with the corresponding literature. We observe a crypto participation of 4.9%, which is similar to the one-digit percentages in Germany found by other studies, for instance, 8% by Exton and Doidge (2018), 7% by Laboure and Jim (2020), 4% by Brandt (2019), or 1% by Hackethal et al. (2021). Moreover, the most determining demographic factors for crypto exposure we identified in our analysis are similar to other studies, i.e., male gender (e.g., Fujiki 2021; Oksanen et al. 2022; Schuh and Shy 2015; Steinmetz et al. 2021), risk-appetite (e.g., Exton and Doidge 2018; Krombholz et al. 2017; Zhao and Zhang 2021), millennials in their 30s (e.g., Bonaparte 2022; Fujiki 2020), or self-employed workers (Fujiki 2020).

Besides similar demographic factors, we also observe similar results for savings and crypto balances. We observe that individuals with higher savings are more likely to have invested in crypto-assets. This is similar to the finding of Bonaparte (2022) who state that individuals with a longer investment time horizon exhibit higher propensities to have invested in crypto-assets. We also find average crypto balances of EUR 3573 that are comparable to Hackethal et al. (2021) who found average balances of EUR 3819. Similar to Steinmetz et al. (2021) and Fujiki (2021), our analysis showed no evidence of any significant effect of being married or being a homeowner on crypto exposure. However, we did not find any relation between crypto ownership and debt. To our knowledge, there is no study that reported a comparable finding.

The incomes of crypto owners in our sample are slightly lower than the incomes of conventional investors and non-investors. In contrast, Fujiki (2021), Hackethal et al. (2021) and Stix (2021) observe that crypto investors are on average richer than non-invested individuals. We observe an average monthly income of EUR 2249, which is slightly different from studies such as Steinmetz et al. (2021) who report an income of EUR 2850, or Hackethal et al. (2021) who observe an income of EUR 5963.[10] Moreover, we observe that income is negatively related to crypto ownership. At first sight, this contradicts Benetton et al. (2021) who found that low-income investors tend to have significantly lower demand for crypto-assets. However, this might be due to the relatively younger individuals in our sample (mean age 35, median age 33) and the fraction of students in our sample is, at 26%, relatively high. Arguably, our income-crypto investment relation seems to be affected by the sample composition since students and younger investors are more likely to be crypto investors while receiving lower incomes.

We provide several complementary insights into the previous literature about the effect of behavioral traits. Considering our crypto participation specification, we observe risk preference as the most robust and positively significant trait, which is comparable to, for instance, Stix (2021). A negative effect is observable in the trait patience, though only with a weak significance which suggests that investors with an impatient trait are more likely to have invested in crypto-assets. This insight has not yet been directly captured by the empirical literature, although it fits well with the results of Oksanen et al. (2022) and Hackethal et al. (2021), highlighting excessive gambling and trading of crypto owners.

In our second specification where we investigated crypto investors at the intensive margin, we only see weakly significant positive effects of patience and effort as well as a negative influence of trust. In particular, the negative relation of trust to the crypto portfolio share is similar to Stix (2021), who found that crypto owners tend to distrust financial institutions. However, Bonaparte (2022) and Krombholz et al. (2017) point out that the decision to invest in crypto-assets requires a certain level of trust in new technologies and third parties to take care of the underlying securities. Thus, our results on the effect of trust have to be interpreted within the appropriate context as our measure of trust is based on 'general trust', which is not necessarily directed towards financial institutions or the respective technology. The effect of different facets of trust on crypto exposure is an important point to consider in future studies. To achieve this, researchers could conduct surveys to obtain responses from participants about the specific factors that influence their level of trust in crypto-assets, including scams, hacks, and tax evasion. Such investigations can provide valuable insights that could inform the development of effective strategies to build and enhance trust in the crypto market. Our significant positive effect for the trait effort is in line with Oksanen et al. (2022) and actually complements their results by highlighting the relation to the intensive margin of crypto exposure in our dataset. The positive effect of patience seems to conflict with our first specification results, although it fits Bonaparte's conclusion (Bonaparte 2022) that crypto investors have a longer investment time horizon. We see these conflicting results as an indication that there is some heterogeneity among crypto investors that have not yet been highlighted enough in the literature. This could include impatient investors seeking fast returns (Hackethal et al. 2021; Oksanen et al. 2022) and more seasoned, patient investors who have been holding crypto-assets for a relatively long period. Unfortunately, we do not have the appropriate variables and sample depth to further distinguish these groups. Notably, this is an opportunity for future research to conduct additional surveys of crypto investors and disentangle the conflicting results in the literature that apparently could be influenced by the composition of the respective data sample.

In the case of the remaining behavioral traits—self-control, loss aversion, and procrastination—we do not find any significant effects in our two specifications. Arguably, the traits might be imprecisely measured as each trait is only based on a few survey questions. Although a measurement error seems unlikely because the effects we measure for the behavioral traits risk, trust, and patience follow the related literature, we further diminish this concern by conducting a robustness check where we estimate a probit regression on stock market participation. The results are displayed in Table A10 in the Appendix B. We observe that self-control and loss-aversion show highly significant coefficients which are conceptually in line with the literature: Self-control is positively, and loss-aversion negatively, related to stock market participation (Dimmock and Kouwenberg 2010; Sekścińska et al. 2021). Notably, this underlines the validity of our results and confidence that self-control, loss aversion, and procrastination are not related to crypto exposure.

Besides our comprehensive behavioral trait analysis, our study also highlights new insights into crypto ownership with respect to demographic factors and consumption. Firstly, we observe that crypto-assets are mostly obtained by students and less often by retirees. As pointed out by McMorrow and Esfahani (2021), stereotypical crypto owners are male, high-income earners, or young students aiming to earn high profits. However, there is no study that clearly shows that students are a prominent group among crypto investors. Furthermore, the effect of being a student disappears as soon as we include significant consumption variables, in this case, food subscriptions. Indeed, food subscriptions are mostly demanded by students[11] and, therefore, serves as a solid proxy. However, we observe that the crypto share in the total portfolio is lower for students, which can arguably be explained by the lower average income of students.

Moreover, we compare the most striking consumption groups between crypto owners, conventional investors, and non-investors. Crypto owners tend to spend more on electronics, capital investments, food subscriptions, taxis, and train tickets, and exhibit higher credit card statements. At the same time, they spend less on pets, refuelling, pharmacy, drugstore, and health insurance, and pay lower rents.[12] Apparently, crypto owners travel more with public transportation, spend less on health care and hygiene and more on investments, electronics, and food delivery. Moreover, they pay smaller rents, which, again, is a typical feature of students. Our regression analysis reveals interest payments and food subscriptions as the most influential determinants of crypto ownership, while drugstore expenses determine the crypto share in the observed portfolios.

Regarding our auxiliary analysis on financial advice preferences, we found mixed evidence. Concerning our analysis of whether respondents have ever consulted a financial advisor in the past, we find a negative, but insignificant coefficient for having crypto-assets. Putting this result into the context of the corresponding literature, we can explain this by the notion that crypto owners tend to be characterized by DIY investment decision-making (Hackethal et al. 2021) and a high financial literacy (Bonaparte 2022; Fujiki 2020). Although we have not elicited financial literacy per se, we still observe that most crypto owners stated to have enough financial literacy in their perception. Relatedly, crypto owners find advisory services to be too time-consuming and of low quality, which further underlines our negative relationship between crypto and financial advice. Nevertheless, further research is needed to validate our findings with more robust results.

In our auxiliary analysis, we also observe that investors who significantly save more are more likely to have invested in crypto-assets. This suggests that they are looking for new investment opportunities and use their available financial resources to invest relatively more in crypto. Although we are not able to observe detailed trading and performance histories, we still see that such investors have increased their total portfolios once they include crypto-assets in their portfolios. For this, we provide further evidence in Table A11 in the Appendix B where we regressed total portfolio size on crypto ownership and further controls.

Our study investigated explanatory variables for crypto ownership. However, we missed an extended analysis concerning additional portfolio measures related to crypto ownership. For example, we did not investigate volatility measures and changes in portfolio construction and how these are affected considering the characteristics and behavioral traits of individual investors. This provides further opportunities for additional research, such as the work of (Floros et al. 2020).

Finally, we point out that the dataset and drawn sample have to be taken with caution. The data is based on a sample that is drawn from a personal finance management app with the aim to help users manage their finances. This app attracts certain types of individuals and, thus, does not necessarily represent the German population. The average age of 35 is remarkably young and the sample contains a relatively large number of students. Additionally, the app requires that users are willing to connect all their bank accounts and security accounts with their individual profiles. The app reminds users to do so, so that we expect to observe more or less complete pictures of their finances and, ultimately, of their crypto holdings. Notably, this is an advantage since other studies rather use data from only one bank (e.g., Hackethal et al. 2021), or even only self-reported data based on surveys (e.g., Fujiki 2021; Steinmetz et al. 2021 or Bonaparte (2022)). We instead observe data from crypto wallets that no other study analyzed so far. Moreover, transactions are all labeled and are hence providing a detailed picture of users' finances. Nevertheless, there could be measurement errors in the underlying labeling mechanisms or self-reporting biases in the respondents' survey answers. Moreover, some of our analyses are based on rather small regression samples and should be confirmed in future research using a higher number of crypto observations over a longer time period, including data from different financial institutions.

5. Conclusions

In this study, we seek to answer the following questions: Who are the crypto owners, and what are additional behavioral and consumption-level determinants? We provide new insights into crypto owners with respect to their demographics, behavioral traits, finances, and consumption. So far, only a few studies have investigated crypto investors in Germany and there is a substantial lack of data coverage. Most of the studies only use survey data or transaction data from one bank. However, since crypto-assets are not directly covered by traditional brokers, these studies are not able to observe true crypto ownership and are reliant on proxies (Hackethal et al. 2021). In comparison, we use a dataset from a personal finance management app, allowing us to identify crypto owners, crypto wallets, and crypto portfolios in a straightforward way.

We find that crypto investors are rather male, risk-seeking, student, or self-employed. Furthermore, they show some degrees of impatience, while the other investigated behavioral traits, trust, self-control, loss-aversion, procrastination, or effort, play no significant roles as determinants for crypto participation. Moreover, crypto participation increases with monthly savings, suggesting that crypto investors look for new investment opportunities and diversify their total portfolio. When investigating the intensive margin, crypto owners increase their crypto share in their portfolio. Most crypto owners have no experience with financial advisory. They see it as too time-consuming and qualitatively poor, and instead, they rather decide on their own as they have self-reported high financial literacy. Lastly, we find that crypto owners show a remarkable consumption profile. For instance, they exhibit higher expenses for electronics, capital investments, food subscriptions, taxis, and train tickets, and more often purchase using credit cards. They spend less on pets, refueling, pharmacy, drugstore, and health insurance, and pay less rent. We conclude that they show typical student profiles who travel more with public transportation and spend less on health but more on electronics, food delivery, and investments. These results are by and large in line with the literature.

Exploiting this unique dataset, our empirical analysis not only validates previous results from the related literature, but also provides novel insights, especially with respect to behavioral traits, consumption profiles, the intensive margin of crypto ownership, and financial advice. As a result, we provide a more comprehensive picture of what determines crypto exposure and highlight the missing consideration of heterogeneity among crypto owners. Our analysis provides a novel insight into the connection between consumption and crypto investment, which has not been explored in the existing literature. By identifying the specific consumption patterns of crypto owners, we contribute to a better understanding of their behavior, motivations, and investment decisions. The findings suggest that crypto owners tend to have unique consumption profiles, which may influence their investment behavior and portfolio diversification. Moreover, we show that consumption data provides several consistently significant determinant variables that can help to identify crypto owners and their portfolio exposure using PSD2 data only.

Our study provides valuable insights that could aid policymakers, tax authorities, and financial institutions in designing suitable regulatory measures and financial products targeting crypto investors. The findings highlight the importance of developing regulations that address the diverse needs and behaviors of crypto owners to ensure fair and effective regulation. We recommend that policymakers and tax authorities implement regulatory measures, such as taxation, anti-money laundering regulations, and investor protection measures, to mitigate the risks associated with crypto ownership. Furthermore, we suggest that targeted measures should be taken to prevent tax evasion by specific groups of crypto investors. This can include providing education and resources to help investors make informed decisions, offering risk-management tools, and developing new investment products that cater to different risk profiles and investment goals. Nevertheless, our findings need to be taken with a grain of salt and should be confirmed with larger and even more comprehensive datasets. Notably, this underlines the need for more endeavored data collection including not only demographic data, but also consumption data, behavioral survey questions, and detailed insights into crypto owner portfolios and trading activities.

Author Contributions: Conceptualization, F.N. and Daniel Weiss; Methodology, F.N. and D.W.; Software, F.N. and D.W.; Validation, F.N. and D.W., Formal Analysis, F.N. and D.W.; Investigation, F.N. and D.W.; Data Curation, F.N. and D.W.; Writing—Original Draft Preparation, F.N. and D.W.; Writing—Review & Editing, F.N. and D.W.; Visualization, F.N. and D.W. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are not publicly available due to data protection agreements.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Survey

The participation in the survey over time is depicted in Figure A1. The overall field phase of the survey proceeded from 9 August until 17 September 2021, and started with a test phase where we tested the customers' response behavior for measurement errors. During the test phase, we did not apply any monetary incentivization, i.e., we asked for voluntary participation in the survey. Since 27 August 2021, the actual field phase started where we activated established customers in charges (first charge on 27 August 2021, second charge on 6 September 2021, etc.). When participating in the survey, we incentivized them to automatically participate in a prize drawing of 50 EUR 20 Amazon vouchers. Since 10 September 2021, we further activated an additional sample which included new customers. The overall net sample size is n = 1771. The winning respondents were drawn on 17 September 2021. After filtering (1) non-completed surveys, (2) surveys with missing responses, (3) surveys with total response durations longer than 60 min, and (4) duplicated participations, we end up with a cleaned net sample size of n = 1761.

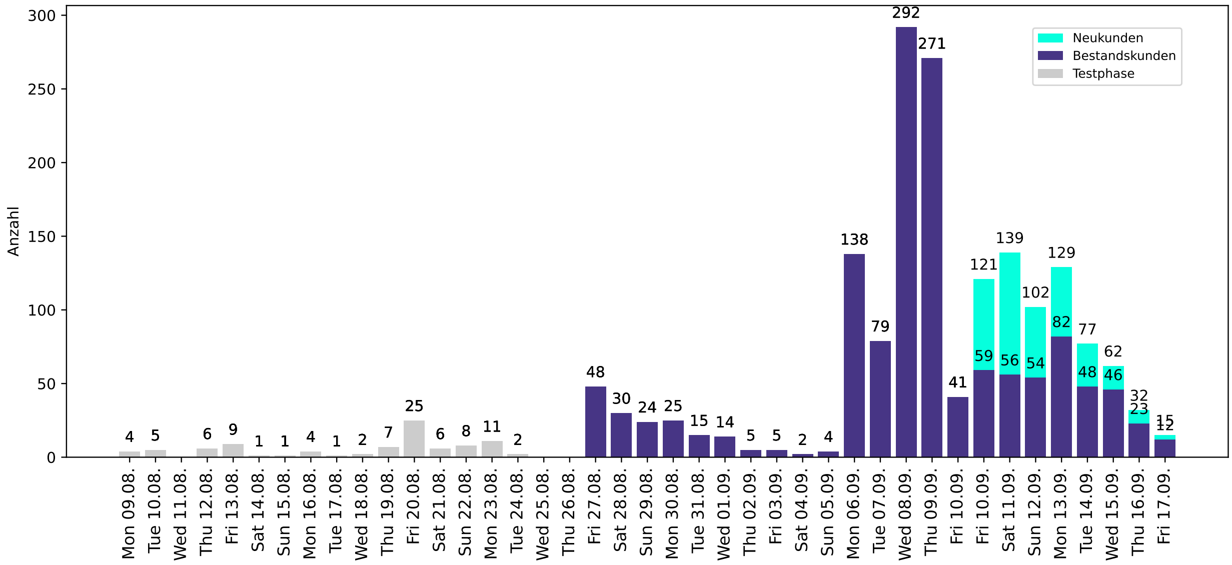

Figure A1. Survey participation of completed surveys over time. **Source:** Own data.

Table A1. Number of cases. **Source:** Own data.

Filter	Sample Size
- users who were activated to the survey	ca. 56,000
- users who participated to the survey	2163
- users who completed survey *	1761
- users with available account transaction data (2018–2022)	1533
- users with available security account data	689

Note: *: We define completed surveys by four filters: (i) non-completed surveys, (ii) surveys with missings in responses, (iii) surveys with total response durations longer than 60 min, and (iv) duplicated participations.

Table A2. Suvey response rates. **Source:** Own data.

	Overall Activated Customers	All Customers		Customers with Completed Questionnaires		
	Number	Number	Response Rate	Number	Dropout Rate	Response Rate
all	ca. 56,000	2163	3.86%	1771	18.12%	3.16%
survey test phase	ca. 5000	118	2.36%	92	22.03%	1.84%
established customers *	ca. 45,000	1684	3.74%	997	40.80%	2.22%
new customers *	ca. 6000	359	5.98%	297	17.27%	4.95%

Note: *: respondents were incentivated with 10 Euros Amazon-vouchers. We define completedness by the four filters: (i) non-completed surveys, (ii) surveys with missings in responses, (iii) surveys with total response durations longer than 60 min, and (iv) duplicated participations.

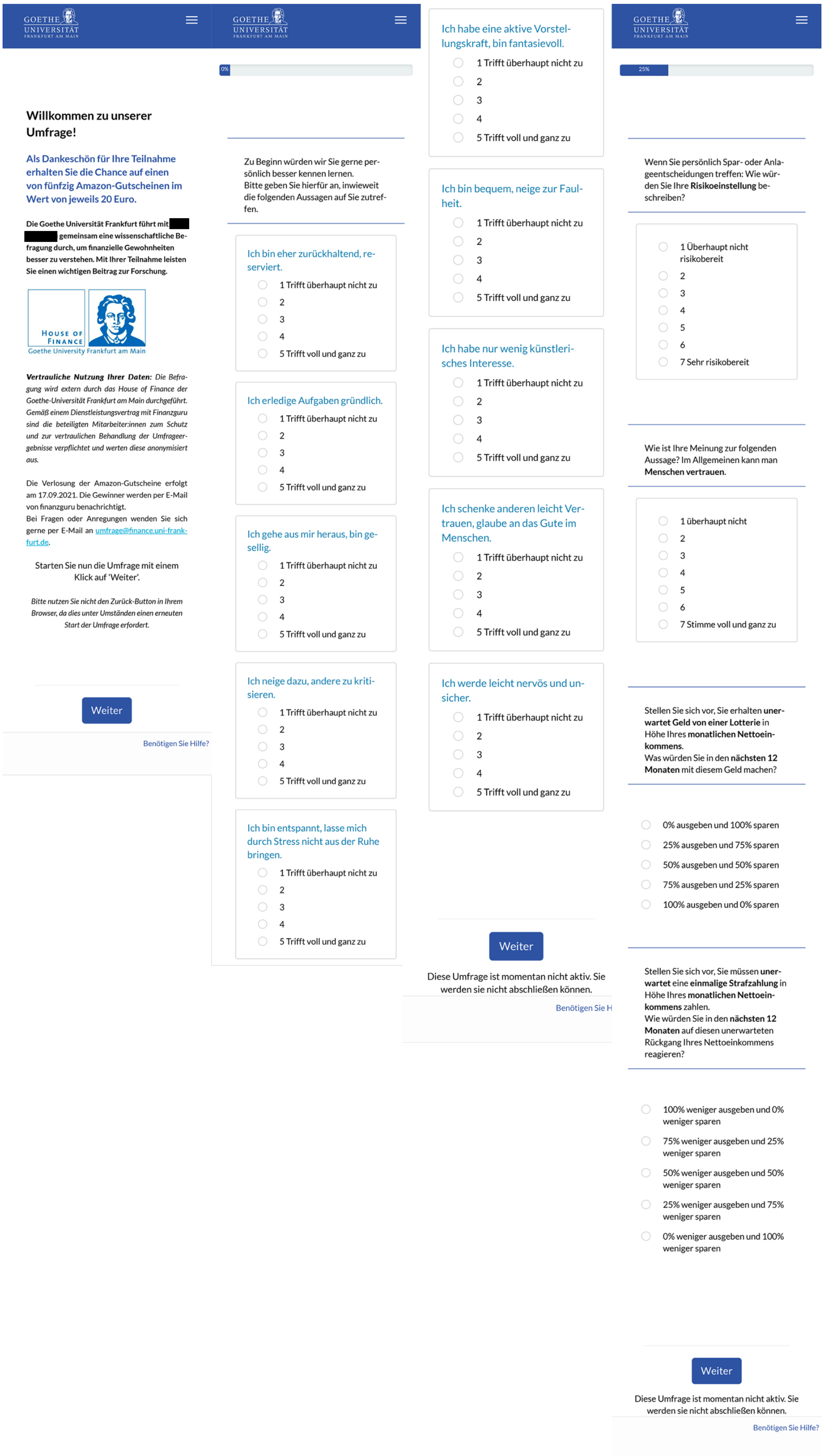

Figure A2. Survey mobile version (page 1–3). **Source:** Own data.

Figure A3. Survey mobile version (page 4–6). **Source:** Own data.

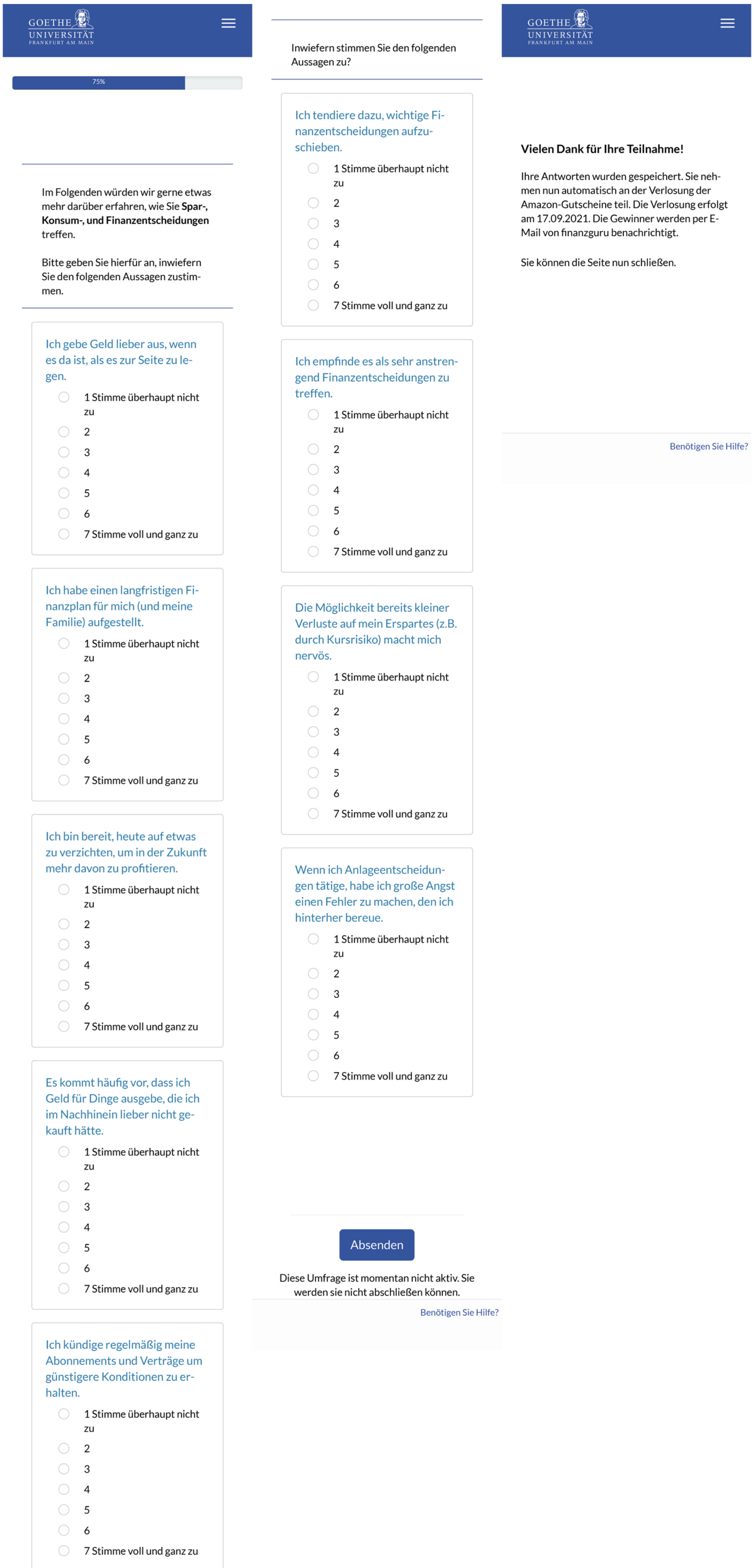

Figure A4. Survey mobile version (page 7–8). **Source:** Own data.

Appendix B

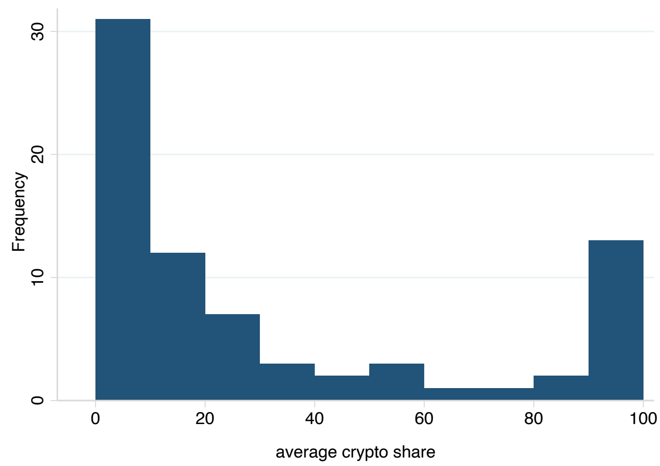

Figure A5. Histogram of average crypto share of crypto owners in their total portfolio. **Note:** Here, we display a histogram of the shares of crypto-assets in users' total portfolios. **Source:** Own data.

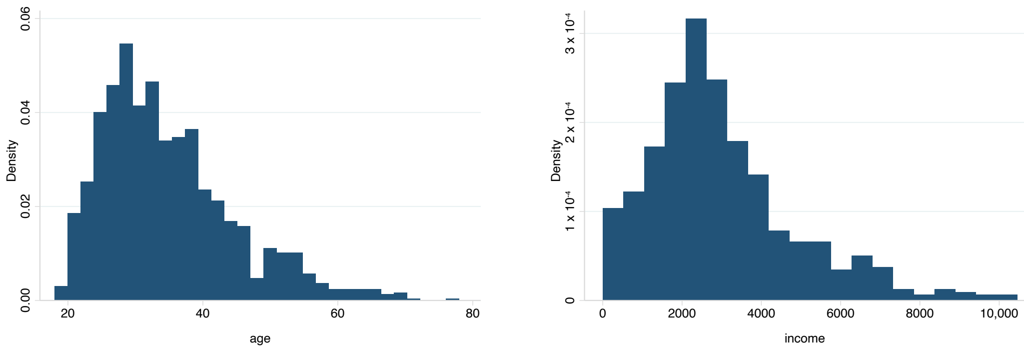

Figure A6. Histograms of age and income. **Source:** Own data.

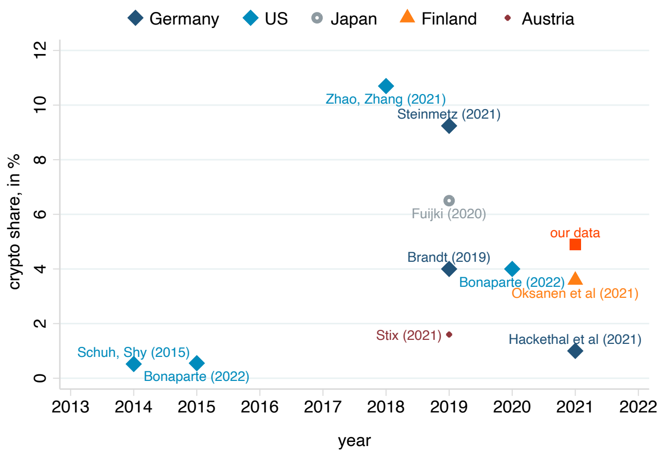

Figure A7. Crypto share found by different studies, by countries. **Note:** Here, we display the crypto share in different countries that were reported by various studies, namely Schuh and Shy (2015), Brandt (2019), Fujiki (2020), Hackethal et al. (2021), Steinmetz (2021), Stix (2021), Zhao and Zhang (2021), Bonaparte (2022), Oksanen et al. (2022). **Source:** Own data.

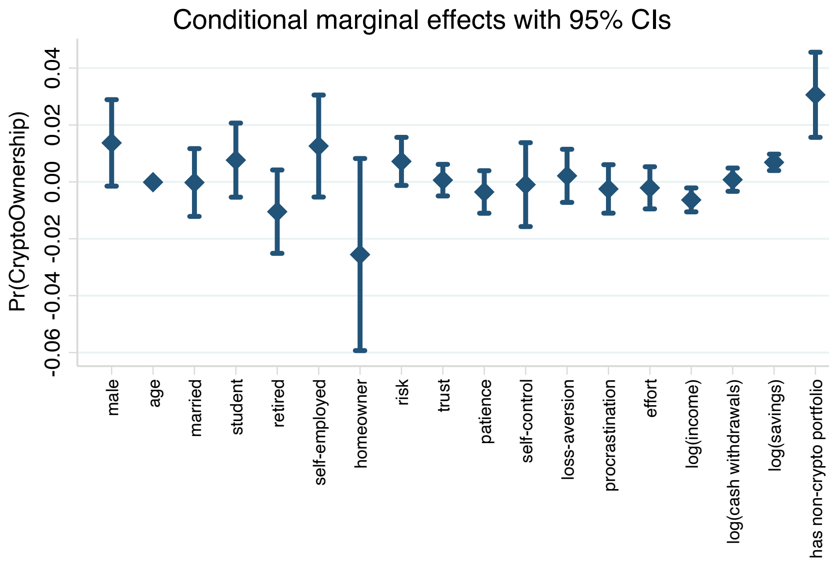

Figure A8. Marginal effects of all covariates in the full model. **Note:** Here, we display the average marginal effects of all covariates that base on the probit regression from Equation (1) where we regressed a dummy that is 1 if an individual holds crypto-assets, and 0 if not. **Source:** Own data.

Table A3. Descriptive statistics of survey and demographics. **Source:** Own data.

	N	Mean	sd	min	max
Survey questions					
I prefer to spend money when it is there then put aside	1531	3.182	1.563	1	7
I have long-term financial plan for myself and my family	1532	4.151	1.991	1	7
I am willing to give up sth. today to profit more in future	1532	3.031	1.520	1	7
It happens often that I spend money on things and regret	1532	4.414	1.717	1	7
I regularly cancel subscrip. and contracts to get better conditions	1532	4.474	2.004	1	7
I tend to postpone important financial decisions	1532	3.139	1.650	1	7
I find it very stressful to make financial decisions	1532	3.636	1.839	1	7
The possibility of small losses on savings makes me nervous	1531	3.273	1.813	1	7
I am afraid of making mistakes that I regret afterwards	1529	3.865	1.821	1	7
Behavioral traits					
risk	1532	3.891	1.552	1	7
trust	1532	3.946	1.377	1	7
patience	1532	3.107	1.317	1	7
self-control	1532	4.346	1.274	1	7
procrastination	1532	3.139	1.650	1	7
effort	1532	3.636	1.839	1	7
loss-aversion	1531	3.569	1.661	1	7
Demographic information					
age	1533	34.73	9.936	18	78
male	1533	0.620	0.486	0	1
married	1533	0.596	0.491	0	1
employed	1533	0.217	0.412	0	1
unemployed	1533	0.472	0.499	0	1
homeowner	1533	0.045	0.207	0	1
retired	1533	0.295	0.456	0	1
student	1533	0.265	0.441	0	1
self-employed	1533	0.114	0.318	0	1

Note: Here, we display the descriptive statistics of the survey responses of the survey questions on behavioral traits, of the behavioral traits, and of the demographic information. Note that we statistically imputed demographic information.

Table A4. Descriptive statistics of imputed vs. non-imputed demographics. **Source:** Own data.

	N	Mean	sd	min	max
male	1312	0.610	0.488	0	1
male (imputed)	1533	0.620	0.486	0	1
age	1124	35.130	10.060	18	78
age (imputed)	1533	34.730	9.936	18	78
employed	972	0.188	0.391	0	1
employed (imputed)	1533	0.217	0.412	0	1
unemployed	972	0.466	0.499	0	1
unemployed (imputed)	1533	0.472	0.499	0	1
married	299	0.625	0.485	0	1
married (imputed)	1533	0.596	0.491	0	1

Note: In this table, we show the imputed statistics in comparison to non-imputed statistics. We applied Stata's *mi impute*-command to impute missing values. In the case of the continuous variable age, we apply multivariate normal regression (mvp Stata command) and for the remaining indicator variables, we apply predictive mean matching (pmm Stata command). Overall, the imputed variable's means do not substantially differ from non-imputed means.

Table A5. Survey questions. **Source:** Own data.

	Behavioral Trait	Survey Question	Original Survey Question in German	Skala
1	risk	If you personally make savings or investment decisions, how would you describe your risk attitude?	Wenn Sie persönlich Spar- oder Anlageentscheidungen treffen: Wie würden Sie Ihre Risikoeinstellung beschreiben?	1 (no risk) to 7 (high risk)
2	trust	What is your opinion on the following statement? In general, people can be trusted.	Wie ist Ihre Meinung zur folgenden Aussage? Im Allgemeinen kann man Menschen vertrauen.	1 (no trust) to 7 (high trust)
3	patience	I would rather spend money when it is there than put it aside.	Ich gebe Geld lieber aus, wenn es da ist, als es zur Seite zu legen.	1 (totally disagree) to 7 (absolutely agree)
4	patience	I am willing to give up something today in order to benefit more in the future.	Ich bin bereit, heute auf etwas zu verzichten, um in der Zukunft mehr davon zu profitieren.	1 (totally disagree) to 7 (absolutely agree)
5	self-control bias	I have created a long-term financial plan for myself (and my family).	Ich habe einen langfristigen Finanzplan für mich (und meine Familie) aufgestellt.	1 (totally disagree) to 7 (absolutely agree)
6	self-control bias	It often happens that I spend money on things that, in hindsight, I would have preferred not to have bought.	Es kommt häufig vor, dass ich Geld für Dinge ausgebe, die ich im Nachhinein lieber nicht gekauft hätte.	1 (totally disagree) to 7 (absolutely agree)
7	self-control bias	I regularly cancel my subscriptions and contracts to get better conditions.	Ich kündige regelmäßig meine Abonnements und Verträge um günstigere Konditionen zu erhalten.	1 (totally disagree) to 7 (absolutely agree)
8	procrastination	I tend to put off important financial decisions.	Ich tendiere dazu, wichtige Finanzentscheidungen aufzuschieben.	1 (totally disagree) to 7 (absolutely agree)
9	effort	I find it very exhausting to make financial decisions.	Ich empfinde es als sehr anstrengend Finanzentscheidungen zu treffen.	1 (totally disagree) to 7 (absolutely agree)
10	loss aversion	The possibility of even small losses on my savings makes me nervous.	Die Möglichkeit bereits kleiner Verluste auf mein Erspartes (z.B. durch Kursrisiko) macht mich nervös.	1 (totally disagree) to 7 (absolutely agree)
11	loss aversion	When making financial decisions, I am afraid of making mistakes that I regret afterwards	Wenn ich Anlageentscheidungen tätige, habe ich große Angst einen Fehler zu machen, den ich hinterher bereue.	1 (totally disagree) to 7 (absolutely agree)

Note: Here, we present the survey questions, both, in English and German and the unterlying behavioral trait of each survey question.

Table A6. Descriptive statistics of bank account transactions and security accounts.

	N	Mean	sd	min	max
Bank Account Information					
number of current accounts	1455	2.29	1.88	0	27
monthly total account transactions	1533	52.89	28.89	0	241
days in overdraft	1455	178.50	370.10	0	4307
number of insurance packages	1533	5.25	4.38	0	21
total debt	1533	−374.50	3976.00	−112,602.00	0.00
current account balance	1453	3493.00	7773.00	−8552.00	80,109.00
Security Account Information					
has security accounts	1533	0.45	0.50	0	1
has crypto wallets	1533	0.05	0.22	0	1
number of depots	1533	1.03	1.99	0	19
number of crypto depots	1533	0.20	1.26	0	17
number of non-crypto depots	1533	0.83	1.30	0	11
total depot balance	1533	13,566.00	87,839.00	−19,950.00	2,788,000.00
total crypto depot balance	1533	174.80	4652.00	0.00	181,058.00
total non-crypto depot balance	1533	13,391.00	87,730.00	−19,950.00	2,788,000.00
share crypto assets	1533	1.36	9.99	0.00	100.00
Monthly Averages per Category					
income	1533	2463.00	1727.00	0.00	10,457.00
cash withdrawals	1533	313.90	297.60	0.00	2780.00
expenses for vocational training	1533	49.90	86.61	0.00	326.70
financial expenses	1533	637.60	917.00	0.00	7792.00
financial receipts	1533	88.88	200.20	0.00	696.40
leisure	1533	88.75	72.64	0.00	609.40
health	1533	72.28	76.56	0.00	652.50
pets	1533	22.26	37.55	0.00	185.00
children	1533	61.94	123.50	0.00	694.00
food	1533	221.90	175.40	0.00	1013.00
holiday	1533	266.10	274.80	0.00	1544.00
shopping	1533	302.30	203.20	0.00	1373.00
savings	1533	398.90	665.00	0.00	4840.00
refueling	1533	81.70	57.55	0.00	341.60
mobility	1533	106.80	89.16	0.00	841.80
insurance	1533	224.50	262.40	0.00	1721.00
living	1533	606.20	473.20	0.00	3152.00
other expenses	1533	1778.00	2231.00	0.00	25,723.00
other receipts	1533	2352.00	2864.00	0.00	35,618.00

Table A7. Means and *t*-tests of crypto owners, conventional and non-investors of survey responses on financial decision-making and financial advice. **Source:** Own data.

	(1) Crypto Investors	(2) Conventional Investors	(3) Non-Invested	(1)–(2) Difference Crypto and Conventional Investors	(1)–(3) Difference Crypto and Non-Invested	(2)–(3) Difference Conventional and Non-Invested
financial advice						
ever asked for financial advice (0 no. 1 yes)	0.43	0.53	0.45	−0.10 *	−0.02	0.08 ***
satisfaction financial advise (1 not satisfied. 7 fully satisfied)	4.69	4.39	4.80	0.29	−0.11	−0.41 ***
survey responses on investment decision-making						
prefer to spend money when it is there then put aside	2.71	2.87	3.45	−0.16	−0.74 ***	−0.58 ***
have long-term financial plan for myself and my family	5.20	4.72	3.65	0.48 **	1.55 ***	1.07 ***
am willing to give up sth. today to profit more in future	2.47	2.89	3.19	−0.42 **	−0.72 ***	−0.3 ***
happens often that I spend money on things and regret	4.65	4.65	4.22	0.00	0.43 **	0.43 ***
regularly cancel subscrip. and contracts to get better conditions	4.60	4.66	4.33	−0.06	0.27	0.34 ***
tend to postpone important financial decisions	2.67	2.93	3.33	−0.26	−0.67 ***	−0.4 ***
find it very stressful to make financial decisions	2.85	3.31	3.95	−0.45 **	−1.09 ***	−0.64 ***
possibility of small losses on savings makes me nervous	2.43	2.74	3.73	−0.32 *	−1.31 ***	−0.99 ***
am afraid of making mistakes that I regret afterwards	3.16	3.39	4.28	−0.23	−1.12 ***	−0.89 ***
n	75	614	844			
received financial advice for following products						
savings products	0.13	0.33	0.45	−0.2 **	−0.32 ***	−0.12 ***
invesmtents	0.69	0.67	0.49	0.01	0.19 **	0.18 ***
pension	0.50	0.60	0.65	−0.1	−0.15 *	−0.05
insurance	0.66	0.61	0.61	0.04	0.05	0.00
loans	0.19	0.17	0.25	0.02	−0.07	−0.08 ***
real estate	0.41	0.37	0.33	0.03	0.07	0.04
n	32	326	376			
reason no financial advice demanded						
no money	0.16	0.24	0.47	−0.08	−0.31 ***	−0.23 ***
too expensive	0.23	0.23	0.26	0.00	−0.03	−0.03
low quality	0.30	0.18	0.10	0.12 *	0.21 ***	0.09 ***
time-consuming	0.35	0.13	0.17	0.22 ***	0.18 ***	−0.04
no trust	0.42	0.40	0.30	0.02	0.12	0.1 ***
enough financial literacy	0.51	0.42	0.16	0.09	0.36 ***	0.26 ***
rather advice of peers	0.16	0.14	0.17	0.02	−0.01	−0.03
n	43	288	467			

Note: In the first three columns we present conditional means of different characteristics and behavioral traits. In the last three columns, we show absolute differences of the means with significance levels 10%, 5%, and 1% indicated by *, **, and *** from a two-sided *t*-test. Survey responses on investment decision-making and satisfaction with financial advice were questioned based on a 7-point Likert scale. One non-investor did not respond to the questions on financial advice.

Table A8. Probit regression on financial advice ever received. **Source:** Own data.

	Ever Asked for Financial Advice				
	(1) Probit	**(2) Probit**	**(3) Probit**	**(4) Probit**	**(5) Probit**
has crypto	−0.116	−0.139	−0.176	−0.175	−0.224
	(0.151)	(0.151)	(0.153)	(0.155)	(0.158)
male	−0.0278	−0.0342		−0.0953	−0.107
	(0.0689)	(0.0692)		(0.0749)	(0.0753)
age	0.0315 ***	0.0310 ***		0.0318 ***	0.0313 ***
	(0.00362)	(0.00371)		(0.00384)	(0.00386)
married	0.0317	0.0120		−0.0782	−0.0749
	(0.0680)	(0.0683)		(0.0715)	(0.0716)
student	−0.0534	−0.0479		−0.0741	−0.0799
	(0.0782)	(0.0809)		(0.0824)	(0.0824)
retired	−0.0699	−0.0522		−0.0662	−0.0560
	(0.0723)	(0.0732)		(0.0741)	(0.0746)
self-employed	0.147	0.194		0.166	0.152
	(0.108)	(0.129)		(0.129)	(0.129)
homeowner	0.130	0.106		0.0797	0.0595
	(0.171)	(0.172)		(0.170)	(0.171)
log(income)		−0.00433		−0.00601	−0.00456
		(0.0224)		(0.0226)	(0.0226)
log(saving)		0.0497 ***		0.0447 ***	0.0446 ***
		(0.0127)		(0.0130)	(0.0130)
log(total debt)		0.00624		0.00589	0.00756
		(0.0135)		(0.0135)	(0.0136)
risk			−0.0004	0.0673 *	0.0547
			(0.0382)	(0.0402)	(0.0409)
trust			0.0844 **	0.0820 **	0.0842 **
			(0.0328)	(0.0337)	(0.0337)
patience			0.110 ***	0.0740 *	0.0792 **
			(0.0372)	(0.0388)	(0.0389)
self-control			0.408 ***	0.330 ***	0.316 ***
			(0.0745)	(0.0788)	(0.0793)
loss aversion			−0.0565	−0.0733	−0.0648
			(0.0515)	(0.0528)	(0.0530)
procrastination			−0.0822 **	−0.0665	−0.0678
			(0.0411)	(0.0424)	(0.0424)
effort			0.161 ***	0.193 ***	0.192 ***
			(0.0445)	(0.0464)	(0.0464)
log(total portfolio balance)					0.0149
					(0.00911)
Constant	−1.131 ***	−1.204 ***	−0.0465	−1.105 ***	−1.138 ***
	(0.140)	(0.206)	(0.0332)	(0.212)	(0.214)
Observations	1532	1532	1532	1532	1532
Pseudo R^2	0.047	0.055	0.025	0.076	0.077

Note: Here, we regress a dummy that is one if the respondent stated that he has asked for financial advice, else zero. The behavioral traits, risk, trust, patience, and procrastination are standardized with mean zero and standard deviation one. Since self-control and loss aversion are based on multiple questions, we retrieved factors from both by applying factor analysis. Income, cash withdrawals, and savings are monthly averages. Robust standard errors are in parentheses. ***, **, and * indicate coefficients that are significant at the 1, 5, and 10% levels, respectively.

Table A9. Probit regression of crypto participation, conditional on being invested. **Source:** Own data.

	Crypto Participation, Conditional on Being Invested					
	(1) Probit	**(2) Probit**	**(3) Probit**	**(4) Probit**	**(5) Probit**	**(6) Probit**
male	0.366 **	0.358 **		0.277	0.372 **	0.293 *
	(0.168)	(0.168)		(0.173)	(0.171)	(0.175)
age	−0.00559	−0.00374		−0.00336	−0.00286	−0.00227
	(0.00733)	(0.00733)		(0.00740)	(0.00732)	(0.00743)
married	0.0253	0.0286		0.0350	0.0356	0.0449
	(0.134)	(0.134)		(0.136)	(0.135)	(0.136)
student	0.220	0.194		0.168	0.216	0.190
	(0.146)	(0.155)		(0.156)	(0.156)	(0.157)
retired	−0.153	−0.164		−0.150	−0.174	−0.154
	(0.159)	(0.162)		(0.160)	(0.160)	(0.159)
self-employed	0.230	0.179		0.182	0.133	0.130
	(0.169)	(0.229)		(0.228)	(0.227)	(0.224)
homeowner	−0.535	−0.559		−0.516	−0.674 *	−0.627 *
	(0.352)	(0.358)		(0.359)	(0.345)	(0.349)
log(income)		−0.0234		−0.0215	−0.00837	−0.00982
		(0.0379)		(0.0375)	(0.0403)	(0.0398)
log(saving)		0.0407		0.0311	0.0397	0.0295
		(0.0262)		(0.0260)	(0.0264)	(0.0261)
log(debt)		−0.0401		−0.0404	−0.0453	−0.0446
		(0.0305)		(0.0304)	(0.0323)	(0.0319)
risk			0.186 **	0.135		0.141
			(0.0907)	(0.0904)		(0.0914)
trust			0.00402	0.0103		0.0141
			(0.0635)	(0.0647)		(0.0665)
patience			−0.122	−0.0847		−0.100
			(0.0798)	(0.0809)		(0.0819)
self-control			−0.0915	−0.0496		−0.0490
			(0.165)	(0.170)		(0.173)
loss aversion			0.0328	0.0567		0.0353
			(0.107)	(0.108)		(0.111)
procrastination			−0.0129	−0.0378		−0.0457
			(0.0884)	(0.0920)		(0.0938)
effort			−0.101	−0.0890		−0.0942
			(0.0867)	(0.0876)		(0.0878)
log(food subscriptions)					0.0864 **	0.108 **
					(0.0414)	(0.0426)
log(rent)					−0.0504 **	−0.0500 **
					(0.0240)	(0.0240)
Constant	−1.415 ***	−1.361 ***	−1.362 ***	−1.393 ***	−1.373 ***	−1.431 ***
	(0.320)	(0.417)	(0.0815)	(0.414)	(0.422)	(0.422)
Observations	689	689	689	689	689	689
Pseudo R^2	0.036	0.045	0.026	0.060	0.060	0.078

Note: Here, we regress a dummy that is one if the respondent is invested in crypto assets, conditional on being invested in crypto or conventional assets. The behavioral traits, risk, trust, patience, and procrastination are standardized with mean zero and standard deviation one. Since self-control and loss aversion are based on multiple questions, we retrieved factors from both by applying factor analysis. The remaining spending categories in logs are monthly averages. Robust standard errors are in parentheses. ***, **, and * indicate coefficients that are significant at the 1, 5, and 10% levels, respectively.

Table A10. Probit Regression of Stock Market Participation. **Source:** Own data.

	Stock Market Participation					
	(1) Probit	(2) Probit	(3) Probit	(4) Probit	(5) Probit	(6) Probit
male	0.640 ***	0.637 ***		0.340 ***	0.568 ***	0.322 ***
	(0.0705)	(0.0708)		(0.0782)	(0.0782)	(0.0852)
age	0.00379	0.00736 **		0.0119 ***	0.00964 **	0.0147 ***
	(0.00353)	(0.00367)		(0.00404)	(0.00389)	(0.00420)
retired	−0.293 ***	−0.321 ***		−0.368 ***	−0.323 ***	−0.364 ***
	(0.0739)	(0.0757)		(0.0789)	(0.0780)	(0.0807)
married	0.0371	0.0421		−0.0678	0.0679	−0.0370
	(0.0692)	(0.0698)		(0.0754)	(0.0717)	(0.0774)
student	0.311 ***	0.257 ***		0.176 **	0.135	0.0731
	(0.0793)	(0.0821)		(0.0850)	(0.0843)	(0.0870)
self-employed	0.657 ***	0.493 ***		0.482 ***	0.449 ***	0.455 ***
	(0.111)	(0.130)		(0.135)	(0.133)	(0.137)
homeowner	0.451 ***	0.419 **		0.373 **	0.373 **	0.351 *
	(0.169)	(0.170)		(0.175)	(0.175)	(0.181)
log(income)		−0.0740 ***		−0.0849 ***	−0.0676 **	−0.0818 **
		(0.0230)		(0.0256)	(0.0314)	(0.0346)
log(saving)		0.0334 **		0.0189	0.0344 ***	0.0208
		(0.0130)		(0.0135)	(0.0132)	(0.0137)
log(debt)		−0.0252 *		−0.0287 **	−0.0308 **	−0.0317 **
		(0.0138)		(0.0145)	(0.0144)	(0.0151)
risk			0.319 ***	0.311 ***		0.306 ***
			(0.0395)	(0.0421)		(0.0430)
trust			0.0129	−0.00306		−0.0316
			(0.0346)	(0.0357)		(0.0360)
patience			−0.0827 **	−0.0846 **		−0.0910 **
			(0.0393)	(0.0408)		(0.0418)
self-control			0.365 ***	0.354 ***		0.305 ***
			(0.0797)	(0.0840)		(0.0851)
loss aversion			−0.224 ***	−0.180 ***		−0.166 ***
			(0.0528)	(0.0550)		(0.0568)
procrastination			0.0329	0.0167		0.00395
			(0.0454)	(0.0471)		(0.0472)
effort			0.0290	0.0655		0.0640
			(0.0464)	(0.0489)		(0.0497)
log(pet)					−0.0616 ***	−0.0504 **
					(0.0209)	(0.0215)
log(refueling)					−0.0748 **	−0.0736 **
					(0.0307)	(0.0316)
log(train ticket)					0.0632 ***	0.0611 ***
					(0.0187)	(0.0193)
log(drugstore)					−0.0736 **	−0.0524
					(0.0336)	(0.0352)
log(interest)					−0.0737 **	−0.0741 **
					(0.0289)	(0.0301)
log(taxi)					0.0707 **	0.0565 *
					(0.0283)	(0.0300)
log(credit card statement)					0.0496 ***	0.0343 **
					(0.0138)	(0.0144)
log(furniture)					0.0411 *	0.0513 **
					(0.0213)	(0.0217)
Constant	−0.776 ***	−0.369 *	−0.158 ***	−0.144	−0.180	−0.0644
	(0.139)	(0.207)	(0.0339)	(0.224)	(0.220)	(0.232)
Observations	1533	1533	1532	1532	1533	1532
Pseudo R^2	0.089	0.097	0.121	0.178	0.134	0.204

Note: Here, we regress a dummy that is one if the respondent is invested in the stock market, else zero. The behavioral traits, risk, trust, patience, and procrastination are standardized with mean zero and standard deviation one. Since self-control and loss aversion are based on multiple questions, we retrieved factors from both by applying factor analysis. The remaining spending categories in logs are monthly averages. Robust standard errors are in parentheses. ***, **, and * indicate coefficients that are significant at the 1, 5, and 10% levels, respectively.

Table A11. OLS regression of portfolio balance including crypto ownership. **Source:** Own data.

	log(Total Portfolio Balance)					
	(1) Probit	**(2) Probit**	**(3) Probit**	**(4) Probit**	**(5) Probit**	**(6) Probit**
has crypto	0.832 ***	0.813 ***	0.544 **	0.579 **	0.773 ***	0.551 **
	(0.276)	(0.277)	(0.275)	(0.273)	(0.269)	(0.270)
male	0.791 ***	0.818 ***		0.403	0.580 *	0.225
	(0.297)	(0.295)		(0.291)	(0.298)	(0.294)
age	0.0281 **	0.0283 *		0.0322 **	0.0295 **	0.0347 **
	(0.0139)	(0.0144)		(0.0142)	(0.0145)	(0.0144)
married	−0.186	−0.163		−0.190	−0.0572	−0.106
	(0.251)	(0.250)		(0.250)	(0.247)	(0.249)
student	0.140	0.219		0.0769	0.0881	−0.0339
	(0.313)	(0.318)		(0.307)	(0.316)	(0.305)
retired	0.104	0.0964		0.0859	0.0936	0.0710
	(0.310)	(0.315)		(0.310)	(0.310)	(0.306)
self-employed	−0.101	0.208		0.253	0.133	0.191
	(0.361)	(0.478)		(0.454)	(0.460)	(0.436)
homeowner	0.530	0.670		0.726	0.485	0.571
	(0.498)	(0.500)		(0.491)	(0.497)	(0.486)
log(income)		0.103		0.0956	0.217 ***	0.200 ***
		(0.0748)		(0.0718)	(0.0791)	(0.0767)
log(saving)		−0.0405		−0.0633	−0.0391	−0.0611
		(0.0489)		(0.0470)	(0.0483)	(0.0465)
log(debt)		−0.114 **		−0.111 **	−0.0921 *	−0.0908 *
		(0.0567)		(0.0555)	(0.0554)	(0.0542)
risk			0.313 *	0.378 **		0.389 **
			(0.161)	(0.163)		(0.166)
trust			−0.206	−0.223 *		−0.253 **
			(0.127)	(0.127)		(0.124)
patience			−0.376 **	−0.388 **		−0.363 **
			(0.154)	(0.156)		(0.153)
self-control			0.517 *	0.456		0.437
			(0.307)	(0.315)		(0.308)
loss aversion			−0.422 *	−0.425 *		−0.402 *
			(0.233)	(0.233)		(0.230)
procrastination			−0.00348	0.0215		0.0399
			(0.166)	(0.167)		(0.166)
effort			−0.120	−0.0771		−0.0486
			(0.182)	(0.180)		(0.180)
log(pet)					−0.249 ***	−0.234 ***
					(0.0849)	(0.0827)
log(health insurance)					0.145 **	0.122 **
					(0.0626)	(0.0615)
log(interest)					−0.201 **	−0.197 **
					(0.0968)	(0.0943)
log(drugstore)					−0.274 ***	−0.230 **
					(0.103)	(0.101)
Constant	5.716 ***	5.118 ***	6.897 ***	5.072 ***	5.505 ***	5.360 ***
	(0.539)	(0.685)	(0.151)	(0.646)	(0.688)	(0.659)
Observations	689	689	689	689	689	689
R-squared	0.028	0.038	0.084	0.110	0.074	0.139

Note: Here, we regress logged total portfolio balance of all invested individuals. The behavioral traits, risk, trust, patience, and procrastination are standardized with mean zero and standard deviation one. Since self-control and loss aversion are based on multiple questions, we retrieved factors from both by applying factor analysis. Income, cash withdrawals, and savings are monthly averages. Robust standard errors are in parentheses. ***, **, and * indicate coefficients that are significant at the 1, 5, and 10% levels, respectively.

Table A12. Transaction labels. **Source:** Own data.

mainCategory	subCategory	mainCategory	subCategory
BARENTNAHMEN	GELDAUTOMAT	SONSTIGE_AUSGABEN	SONSTIGE_AUSGABEN
BILDUNG_BERUF	GEWERKSCHAFTEN	SONSTIGE_EINNAHMEN	BARGELDEINZAHLUNG
BILDUNG_BERUF	HOCHSCHULE	SONSTIGE_EINNAHMEN	ERSTATTUNGEN
BILDUNG_BERUF	SONSTIGE_AUSGABEN_BILDUNG_BERUF	SONSTIGE_EINNAHMEN	KAUTION_GUTSCHRIFT
BILDUNG_BERUF	STUDIENGEBUEHREN	SONSTIGE_EINNAHMEN	KREDITAUSZAHLUNG
DROGERIE	DROGERIE	SONSTIGE_EINNAHMEN	RUECKLASTSCHRIFT
EINKOMMEN	BEIHILFE	SONSTIGE_EINNAHMEN	SONSTIGE_EINNAHMEN
EINKOMMEN	ELTERNGELD	SONSTIGE_EINNAHMEN	UNTERHALT_GUTSCHRIFT
EINKOMMEN	KAPITALERTRAEGE	SONSTIGE_EINNAHMEN	VERKAUFSERLOES
EINKOMMEN	KINDERGELD	SPAREN_VORSORGE	ALTERSVORSORGE
EINKOMMEN	LEISTUNGEN_DER_BUNDESAGENTUR_FUER_ARBEIT	SPAREN_VORSORGE	AUFRUNDEN
EINKOMMEN	LOHN_GEHALT	SPAREN_VORSORGE	BAUSPARVERTRAG
EINKOMMEN	MIETEINNAHMEN	SPAREN_VORSORGE	KAPITALANLAGE
EINKOMMEN	RENTE_PENSION	SPAREN_VORSORGE	SPAREN
EINKOMMEN	SELBSTSTAENDIGKEIT	TANKEN	TANKEN
EINKOMMEN	SONSTIGES_EINKOMMEN	VERKEHR_MOBILITAET	AUTOMOBILCLUB
EINKOMMEN	STUDIENGELD	VERKEHR_MOBILITAET	AUTOVERMIETUNG
EINKOMMEN	TASCHENGELD_GUTSCHRIFT	VERKEHR_MOBILITAET	BAHNCARD
ESSEN_TRINKEN	KANTINE	VERKEHR_MOBILITAET	BAHNTICKETS
ESSEN_TRINKEN	LIEFERSERVICE	VERKEHR_MOBILITAET	FAHRRAD
ESSEN_TRINKEN	RESTAURANT	VERKEHR_MOBILITAET	FERNBUS
ESSEN_TRINKEN	SONSTIGE_ESSEN_TRINKEN	VERKEHR_MOBILITAET	KFZ_STEUER
FINANZEN	BAUFINANZIERUNG	VERKEHR_MOBILITAET	OEPNV
FINANZEN	HYPOTHEK	VERKEHR_MOBILITAET	PARKEN
FINANZEN	INKASSO	VERKEHR_MOBILITAET	SHARING_ANGEBOTE
FINANZEN	KREDIT	VERKEHR_MOBILITAET	SONSTIGE_VERKEHRSAUSGABEN
FINANZEN	KREDITKARTENABRECHNUNG	VERKEHR_MOBILITAET	TAXI
FINANZEN	LEASING	VERKEHR_MOBILITAET	WERKSTATT_SERVICE
FINANZEN	SONDERTILGUNG	VERSICHERUNGEN	BERUFSUNFAEHIGKEITSVERSICHERUNG
FINANZEN	SONSTIGE_FINANZAUSGABEN	VERSICHERUNGEN	BRILLENVERSICHERUNG
FINANZEN	SPENDE	VERSICHERUNGEN	GEBAEUDEVERSICHERUNG
FINANZEN	STEUERN_ABGABEN	VERSICHERUNGEN	GERAETEVERSICHERUNG
FINANZEN	ZINSEN_ENTGELTE	VERSICHERUNGEN	GESETZLICHE_KRANKENVERSICHERUNG
FREIZEIT_UNTERHALTUNG	BUECHER_MEDIEN	VERSICHERUNGEN	HAFTPFLICHTVERSICHERUNG
FREIZEIT_UNTERHALTUNG	FITNESSSTUDIO	VERSICHERUNGEN	HAUSRATVERSICHERUNG
FREIZEIT_UNTERHALTUNG	FRISEUR	VERSICHERUNGEN	HAUSTIERVERSICHERUNG
FREIZEIT_UNTERHALTUNG	KINO	VERSICHERUNGEN	KFZ_VERSICHERUNG
FREIZEIT_UNTERHALTUNG	LOTTERIE	VERSICHERUNGEN	KRANKENVERSICHERUNG
FREIZEIT_UNTERHALTUNG	SONSTIGE_FREIZEITAUSGABEN	VERSICHERUNGEN	KRANKENZUSATZVERSICHERUNG
FREIZEIT_UNTERHALTUNG	SPORT	VERSICHERUNGEN	LEBENSVERSICHERUNG
FREIZEIT_UNTERHALTUNG	STREAMING_PAYTV	VERSICHERUNGEN	PFLEGEVERSICHERUNG
FREIZEIT_UNTERHALTUNG	TICKETS	VERSICHERUNGEN	RECHTSSCHUTZVERSICHERUNG
FREIZEIT_UNTERHALTUNG	VEREIN_SONSTIGE	VERSICHERUNGEN	REISEKRANKENVERSICHERUNG
FREIZEIT_UNTERHALTUNG	VEREIN_SPORT	VERSICHERUNGEN	RENTENVERSICHERUNG
FREIZEIT_UNTERHALTUNG	VERLAG_ZEITUNG	VERSICHERUNGEN	RISIKO_LEBENSVERSICHERUNG
FREIZEIT_UNTERHALTUNG	VIRTUELLE_GUETER	VERSICHERUNGEN	SONSTIGE_SACHVERSICHERUNG
GESUNDHEIT	APOTHEKE	VERSICHERUNGEN	SONSTIGE_VERSICHERUNGEN
GESUNDHEIT	ARZT	VERSICHERUNGEN	UNFALLVERSICHERUNG
GESUNDHEIT	AUGENOPTIK	VERSICHERUNGEN	ZAHNZUSATZVERSICHERUNG
GESUNDHEIT	SONSTIGE_GESUNDHEITSAUSGABEN	WOHNEN_HAUSHALT	ABFALLBESEITIGUNG
HAUSTIERE	SONSTIGE_TIERAUSGABEN	WOHNEN_HAUSHALT	BAUMARKT
HAUSTIERE	TIERARZT	WOHNEN_HAUSHALT	DOMAIN_HOSTING
HAUSTIERE	TIERBEDARF	WOHNEN_HAUSHALT	EINRICHTUNG
KINDER	KINDERGARTEN	WOHNEN_HAUSHALT	GAS
KINDER	SCHULE	WOHNEN_HAUSHALT	GRUNDBESITZABGABEN
KINDER	SONSTIGE_KINDERAUSGABEN	WOHNEN_HAUSHALT	HANDWERKSLEISTUNGEN
KINDER	SPIELSACHEN	WOHNEN_HAUSHALT	HAUSGELD
KINDER	TASCHENGELD	WOHNEN_HAUSHALT	INTERNET_TELEFON
KINDER	UNTERHALT	WOHNEN_HAUSHALT	KAUTION
LEBENSMITTEL	GETRAENKEHANDEL	WOHNEN_HAUSHALT	MIETE
LEBENSMITTEL	LEBENSMITTEL_ABO	WOHNEN_HAUSHALT	MOBILFUNK
LEBENSMITTEL	SONSTIGE_LEBENSMITTELAUSGABEN	WOHNEN_HAUSHALT	OEL
LEBENSMITTEL	SUPERMARKT	WOHNEN_HAUSHALT	RUNDFUNKGEBUEHREN
REISEN_URLAUB	AUSLANDSEINSATZENTGELT	WOHNEN_HAUSHALT	SONSTIGE_HAUSHALTSAUSGABEN
REISEN_URLAUB	FLUEGE	WOHNEN_HAUSHALT	STROM
REISEN_URLAUB	HOTEL_URLAUBSWOHNUNG	WOHNEN_HAUSHALT	WASSER
REISEN_URLAUB	SONSTIGE_URLAUBSAUSGABEN		
SHOPPING	BEKLEIDUNGSHANDEL		
SHOPPING	BLUMENHANDEL		
SHOPPING	ELEKTROHANDEL		
SHOPPING	KAUFHAUS_GEMISCHT		
SHOPPING	PRIME_MITGLIEDSCHAFT		
SHOPPING	SONSTIGE_SHOPPING		
SHOPPING	VERSANDHANDEL		

Note: Here, we list all labels of the transaction data that we receive from the cooperating company of their users among who we conducted the survey.

Table A13. Frequencies of crypto wallets & conventional security account. **Source:** Own data.

Name	Crypto Wallet	Conventional Security Account	Total
coinbase	152	0	152
Deutsche Kreditbank	0	125	125
Trade Republic	0	123	123
ING	0	113	113
Comdirect	0	91	91
Sparkasse	0	85	85
(unknown)	26	81	107
Deutsche Bank	0	73	73
Baader Bank	0	69	69
Consorsbank	0	57	57
European Bank for Financial Services	0	25	25
Commerzbank	0	23	23
Union Investment	0	21	21
MLP Banking	0	13	13
flatex Bank	0	13	13
DWS	0	11	11
Volksbank	0	11	11
SSK	0	9	9
apoBank	0	8	8
bitpanda	27	8	35
FIL Fondsbank	0	7	7
binance	5	0	5
DekaBank	0	5	5
VR Bank	0	5	5
Raiffeisenbank	0	4	4
kraken	3	0	3
1822direkt	0	3	3
Hypovereinsbank	0	3	3
DZ BANK	0	2	2
Degussa	0	2	2
LSK Oldenburg	0	2	2
Postbank	0	2	2
GENO Broker	0	1	1
LBBW	0	1	1
Oldenburgische Landesbank AG	0	1	1
VR-Bank Main-Rhön	0	1	1
netbank	0	1	1
Total	**213**	**999**	**1212**

Note: Here, we list a frequency table of bank names from which we observe crypto wallets and security accounts; blue: crypto wallets.

Table A14. Top ten cryptocurrency exchanges ranked by volume CoinMarketCap (2022) https://coinmarketcap.com/rankings/exchanges/, accessed on 29 August 2022.

#	Name	Exchange Score	Volume (24 h)	Avg. Liquidity	Weekly Visits	# Markets	# Coins
1	Binance	9.9	$11,797,432,757 24.44%	894	17,867,235	1702	387
2	Coinbase Exchange	8.2	$1,724,983,926 43.38%	748	1,654,519	585	214
3	FTX	8.1	$1,487,619,359 32.39%	722	3,327,062	423	286
4	Kraken	7.5	$415,574,757 72.56%	717	1,205,310	619	205

Table A14. *Cont.*

#	Name	Exchange Score	Volume (24 h)	Avg. Liquidity	Weekly Visits	# Markets	# Coins
5	Binance.US	7.2	$276,049,818 0.67%	679	459,341	286	131
6	KuCoin	7.2	$662,624,108 29.92%	562	2,296,501	1356	731
7	Gate.io	7.0	$638,662,090 21.36%	530	1,883,413	2455	1477
8	Bitfinex	7.0	$229,170,831 2.55%	628	638,900	378	171
9	Huobi Global	6.8	$558,086,311 20.52%	508	784,470	1094	593
10	Bitstamp	6.6	$119,897,123 120.54%	577	372,366	157	66

Notes

1. We control for different socio-demographic factors such as gender, age, or employment status.
2. The company selected customers who are actively using the app, i.e., logging in to the app regularly. We further identified active users who have all main account flows available such as income, consumption, etc.
3. For a detailed overview of the participation rates and the number of cases, refer to Table A2 in the Appendix A.
4. The descriptive statistics of imputed and non-imputed variables are listed in Table A4 in the Appendix B.
5. For a detailed list of all transaction labels, refer to Table A12. Also, the descriptive statistics of the data sources are displayed in Tables A3 and A6 in the Appendix B.
6. For more details, see Table A13. Note that one user can have multiple security accounts and crypto wallets so that the total number of all accounts and wallets is higher than the sample. Notably, almost all crypto users in our sample also hold conventional assets. Comparing our observed crypto wallets with the largest crypto providers shown in Table A14, we see that our data exhibits good coverage.
7. On average, we observe 6.4 security accounts that divide into an average of 4.1 crypto wallets and 2.3 conventional security accounts.
8. This number is quite similar to the average crypto wallet size of EUR 3819 Hackethal et al. (2021) find in their German online bank data.
9. Note that some of these studies rather refer to *anxiety* or to *stress* which is related to effort.
10. In the case of Hackethal et al. (2021), we explain this by the fact that the underlying sample of their study contains older and high-income investors that are attracted by the bank their data is based on. Also, the mean income observed in our sample is close to that of the German population, which was about EUR 2165 in 2021 (Statistisches Bundesamt (Destatis) 2022).
11. In a consumption study of the German population in 2021, VuMA (2022) reports that about 24.6% of students ordered food several times in a month, while the percentage among the German population lies at 11.5.
12. See note 1 above.

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