**Master Thesis U.S.E.**

# Understanding the economic preferences and personal traits of cryptocurrency investors


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**Abstract**

Since 2009, when Bitcoin's operations began, individuals, the media, and politicians have shown a growing interest in cryptocurrencies. However, little is known about the investors these financial products attract. Using surveys, I investigate and explain the characteristics of individuals who invest in cryptocurrencies relative to investors in traditional assets and the general population. The majority of cryptocurrency investors are young men with high conscientiousness and openness but low extroversion.



**Keywords:** cryptocurrencies, bitcoin, demographics, stock market participation

**JEL CLASSIFICATIONS:** G11 G4

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## 1. Introduction

In spite of the fact that cryptocurrencies have been there since the first Bitcoin was mined in 2009 (George, 2016), they have only lately began to get significant attention from the media as well as from individual households, financial institutions, governments, and regulatory authorities. Despite warnings from the European Banking Authority or national supervisory authorities all over the world such as Algeria, Morocco and China, against "buying, holding, or selling virtual currencies," an increasing number of individual investors have chosen to participate in the market as a result of significant price growth and volatility, particularly toward the end of 2017. (European Central Bank, 2015; European Banking Authority, 2014). Despite the increased interest in cryptocurrencies among the general public, little research has been done on the issue thus far (Cheah and Fry, 2015). Numerous research have started to study Bitcoin's potential as a hedge and its impact in portfolio diversification (Baur et al., 2018; Bouri et al., 2017; Brière et al., 2015; Dyhrberg, 2016), the role of these assets as currencies (Weber, 2016; Yermack, 2013), the emergence of price bubbles in the market (Cheah and Fry, 2015; Corbet et al., 2018) and market price movements in relation to speculation and insider trading (Baek and Elbeck, 2015; Feng et al., 2017; Gandal et al., 2017; Griffin and Shams, 2018). The available evidence suggests that Bitcoin's high volatility and trading volume have also drawn the attention of retail investors (Urquhart, 2018); however, information about the characteristics and behavior of individual investors who choose to buy and trade cryptocurrencies is still relatively scarce. One factor for the paucity of empirical study in this field is the fact that cryptocurrencies are essentially anonymous in their operation. It is one of the biggest benefits, as well as one of the most vocal criticisms, that people may keep and trade these instruments without having a direct connection to a bank account or investment profile.

This thesis is more closely related to Lammer (2020) and Holmen et al. (2018), although it differs in a number of ways. First, whereas Lammer (2018) focuses on the investing behavior of individuals who invest in cryptocurrencies through structured retail products and Holmen (2018) focuses on economic preferences and personality traits among finance professionals and the General Population, I analyze cryptocurrency investors based on their economic decisions, psychological traits and demographics. To be more specific, I consider demographics statistics, techniques from Big-Five personality dimensions as Holmen et al. (2018) did for stock investors, Multiple Price List (MPL) methods by Falk et al. (2016) with "staircase" procedure (Cornsweet, 1962), to induce a degree of patience, a simple lottery choice problem from Fehr and Goette (2007), which allows me to evaluate loss aversion, and finally an experimental technique given by Noussair et al (2014) for their risk attitudes. I will attempt to fill this void in the existing literature and shed light on economic preferences such as time, risk, and loss aversion by correlating industry-relevant economic preferences and personality traits of cryptocurrency investors with those of a random sample of stock market investors or the general working population (henceforth referred to as the "general population sample").

It is vital to evaluate the characteristics of cryptocurrency investors for a number of reasons. No publicly available data explores the characteristics of (potential) cryptocurrency investors; therefore, this work could be a natural addition to a large body of knowledge by providing a portrait of crypto investors and examining whether they are fundamentally different from investors in traditional assets and people who have not or do not to invest in any type of asset in the near future. Understanding these patterns of adoption is essential for regulators and the financial industry. In order for researchers, policymakers, and financial institutions to make accurate predictions in the future, it is essential from a consumer financial protection and normative perspective that research examine the economic preferences and personal characteristics of new investors associated with the adoption of new products and technologies. In addition, I emphasize the significance of adjusting for socioeconomic background variables when comparing the cryptocurrency investors to that of other specific topic pools. Evidently, the broad implications of my thesis would be different if I hadn't accounted for the diversity in socioeconomic factors across individuals. Notable is the fact that a small set of conventional socioeconomic variables significantly reduces variations between respondent pools.

The remaining sections of the paper are organized as follows. Section 2 expands on the background of cryptocurrencies, while Section 3 examines the relevant literature and develops hypotheses. Then, I give experimental design in part 4, variables explanation in section 5, thesis outcomes in section 6, and a thesis conclusion in section 7.

## 2. Background

Cryptocurrencies, according to Nian and Chuen (2015), are "...a peer-to-peer form of electronic currency." It enables internet payments to be made directly between parties without the need of a banking institution. The network uses cryptographic proof of work to time stamp transactions." By contrast, the European Parliament defines cryptocurrencies as "...digital assets that are not issued by a central bank, credit institution, e-money institution, or public authority, that can be used as a medium of exchange or investment in certain circumstances, are exchanged electronically, and do not exist in physical form" (European Parliament, 2022). Inherent in the latter definition is the belief that cryptocurrencies are not a type of money (including electronic money) as defined by economic theory or law, lack legal status or a different legal framework, and are unregulated (European Central Bank, 2015). They are extremely speculative, exposing investors to the risk of significant losses. In January 2022, there were "about 5,600 sorts of crypto assets (although the most majority are not utilized) with an estimated worldwide worth of 2,48 trillion USD (still a tiny fraction of the total value of money) (European Parliament, 2022). Bitcoin is the most well-known cryptocurrency, having the biggest market capitalization over 800 USD billion at the time of writing (Bonneau et al., 2015; CoinMarketCap, 2022).

Bitcoin was launched in 2008 by the pseudonymous Satoshi Nakamoto (whose identity remains unknown) and has been operational since 2009, when the first Bitcoins were mined (Weber, 2016). Bitcoin is a network that enables the anonymous transmission of virtual Bitcoins between users without the assistance of a central entity. Additionally, Bitcoin is not subject to legal or regulatory regulation (Baur et al., 2018), all transactions are validated and documented decentralized by the network's computers (Weber, 2016). If the decentralized network reaches agreement on the transaction's authenticity, a new block is added to the chain of recorded transactions, the so-called blockchain. Thus, the prospect for double-spending Bitcoins is eliminated (George, 2016), since the chain is immutable and thus resistant to manipulation (Glaser et al., 2014). The process of mining generates new Bitcoins, and the maximum quantity is intentionally capped to 21 million (Bouri et al., 2017; George, 2016). Bitcoins are generated by "miners" who solve cryptographic puzzles and validate transactions successfully (Brière et al., 2015). Bitcoin replicates the behavior of natural resources via this mechanism and protocol-based scarcity. Bitcoin proponents see it as a viable alternative to current government-backed currencies, which is of particular importance in the aftermath of the recent financial crisis (Cheah and Fry, 2015).

Bitcoins' qualities include a number of pros and cons. On the one hand, Bitcoin, as the European Central Bank (2015) argues, presents a threat to traditional online payment options because to its low cost structure, worldwide access, and anonymity. Additionally, Bitcoins enable quick and affordable transactions, therefore promoting financial inclusion (European Banking Authority, 2014). By contrast, the European Banking Authority has identified over 70 dangers related with Bitcoins (European Banking Authority, 2014). Money laundering and black market operations are conceivable due to the absence of official control and the high level of anonymity (Baek and Elbeck, 2015). Additionally, there is a strong reliance on technology and networks, a narrow range of payment acceptance, and a high level of volatility and fraud risk (European Central Bank, 2015). Currently, consumers are not safeguarded against these dangers (European Central Bank, 2015). Foley et al. (2018) underscore the need of regulation further by demonstrating that around 25% of Bitcoin users and 44% of transactions are involved with unlawful behavior.

Since 2009, Bitcoin has piqued the media's and general public's curiosity and established itself as the dominant cryptocurrency (European Central Bank, 2015). Despite the collapse of the Mt. Gox exchange in 2014, hacking assaults, and the Chinese government's decision to shut down Bitcoin exchanges (Wildau, 2017), Bitcoin values increased hugely from 2013 to 2021, particularly during the covid-19 pandemic. A Bitcoin was worth roughly 130 USD in the beginning of 2013, nearly 7,571.62 USD at the end of 2019 before the World Health Organization (WHO) proclaimed a Public Health Emergency of International Concern, and around 56,907.96 USD by the end of 2021. Prices increased to an all-time high of almost 68,000 USD on November 10 in 2021 (Time, 2021). This event drew widespread attention and substantial inflows of private capital - despite warnings of an impending bubble (Baur et al., 2018; European Banking Authority, 2014; European Central Bank, 2015), and it may contradict the concept that Bitcoins have no inherent worth (Christopher, 2014). Bitcoins gain value only as a result of user belief or speculation. Additionally, research publications suggest that Bitcoins exhibit bubble tendencies (Corbet et al., 2018). Regulating Bitcoins has been a rare occurrence so far. In 2013, the European Banking Authority warned customers about the dangers of

Bitcoins. This warning was reiterated in 2014, and banks were urged to prevent consumers from purchasing, storing, or trading Bitcoins (European Banking Authority, 2014). The European Union rejected a proposed regulation on March 14 that would have prohibited the cryptocurrency Bitcoin throughout the EU, but instead recommended new restrictions to safeguard consumers and make mining more sustainable (European Parliament, 2022).

However, no official regulation exists in Europe at the time, in part because the European Banking Authority believes that addressing these risks "would need a considerable body of legislation" (European Banking Authority, 2014). Additionally, international rules vary. Certain nations have taken aggressive steps, while others have sought to broaden banking standards to include cryptocurrencies. For example, China prohibits initial coin offerings (ICOs), exchanges, and mining activities. Cryptocurrency sales and purchases are also prohibited in India and a number of other nations, including Egypt, Bolivia, Nepal, and Bangladesh. Individuals can trade on exchanges in South Korea, but only using their genuine names and after their identities have been validated (Library of Congress, 2018; Comply Advantage, 2022). Banking regulators in the majority of Western nations warn of the dangers, yet the actions remain legal (The Law Library of Congress, 2018). In September 2021, El Salvador became the first country to recognize Bitcoin as legal money, despite the International Monetary Fund's (IMF) warning that El Salvador should reverse its decision due to "significant risks associated with the use of Bitcoin on financial stability, financial integrity, and consumer protection" (BBC, 2022).

Given that Bitcoin has developed into a significant new investment class (Goldman Sachs, 2021), a highly valued asset in 2020 (Samm, 2021), and its fast expansion, despite regulator warnings, evaluating the characteristics of cryptocurrency investors is critical for a variety of reasons.

## 3. Literature and Hypothesis development

### 3.1. Time preferences in existing literature

At the moment, little is known about Bitcoin and other cryptocurrency users and investors, owing mostly to a lack of systematic data collecting and the high expense of identifying individuals (Yelowitz and Wilson, 2015). On the one side, several studies demonstrate that Bitcoin investors have significantly different characteristics than traditional investors, including a younger age (Bohr and Bashir, 2014), irrational optimism over easy wealth (Pezzani, 2018), a higher risk propensity (Conlon and McGee, 2020), and the fear of missing out (FoMO) psychological phenomenon (Pichet, 2017). On the other side, due to the risky nature of cryptocurrency investments, they might attract the same types of investors as lottery stocks (Kumar, 2009) and penny stocks (Leuz et al., 2018), those who like gambling (Dorn Jones et al., 2015) or who view trading as a kind of fun (Dorn and Sengmueller, 2009). Dorn Jones, Dorn, and Sengmueller (2015) demonstrate that male, blue-collar investors are more prone to gamble than other investors. Kumar (2009) indicates that lottery-type equities are mostly owned by younger, less affluent, less educated, nonprofessional single males. According to Hasso et al. (2019), males are more likely than women to trade cryptocurrencies due to females are more risk averse (Eckel and Grossman, 2002). Additionally, early research indicates that people retain Bitcoins primarily as a form of currency or for recreational purposes (Grinberg, 2012). In comparison, survey results indicate that many users use Bitcoins for investing goals (Bohr and Bashir, 2014; Smyth, 2013), and that new users retain Bitcoins in their wallets for lengthy periods of time (Glaser et al., 2014). It is possible that the continuous price growth, market qualities such as simple internet access, easy subscription and certification procedures, and 24 hour availability have boosted the number of customers purchasing Bitcoins to earn a high rate of return on investment, Hasso et al. (2019) also observe this consequence. Due to the paucity of comprehensive research on the factors that influence Bitcoin investors, I analyze studies on the share market, which is well-established, popular, and most analogous to the Bitcoin market. It is feasible to determine the characteristics of cryptocurrency investors by looking at the difference between cryptocurrency investors and share investors using the elements that influence share investors. Several financial studies indicate that choices involving trade-offs between instant satisfaction and later rewards are critical to life outcomes. Patience has been found as a significant factor in life success. More patient communities are proved to be wealthier (Dohmen et al., 2017; Falk et al., 2018), and more patient individuals are able to acquire more skills, earn more money, and have better health (Borghans and Golsteyn, 2006; Sutter et al., 2013, Golsteyn et al., 2014). More patient people are more prepared to forego immediate enjoyment in exchange for greater gratification at a future date. In economics, time preferences describe how individuals make intertemporal consumption trade-offs. A basic view of the universe, which is at the core of typical economic models, claims that humans comprehend benefit in the present and the future with equal acuity. However, this would need that person have the ability to visualize the future, and hence the usefulness of future payments. Nevertheless, data from psychology, neurology, and economics suggests that future incentives are more difficult to comprehend and visualize than present rewards, since one must concentrate on goal-relevant information and integrate abstract knowledge (e.g., Carpenter, Just, & Shell, 1990; Gottfredson, 1997). I hypothesize the following based on the available literature:

**Hypothesis 1:** Crypto investors have longer term preferences than stock investors.

### 3.2. Loss aversion in existing literature

There have been several recent publications examine the impact of loss aversion in financial economics (Benartzi & Thaler, 1995; Barberis, Huang, & Santos 2001; Gomes, 2005). Benartzi and Thaler (1995) demonstrate that people who do not invest in the stock market can develop loss aversion, hence a sizable portion of the population does not own stocks (see, for example, Mankiw & Zeldes, 1991). According to Benartzi and Thaler, individuals are averse to investing in stocks and other types of assets owing to a combination of loss aversion and a limited planning horizon hence this could happen for cryptocurrencies too. Additionally, loss aversion has been linked to several economic occurrences that are difficult to analyze under the idea of reference-point independence. Examples include financial market behavior (Odean 1998; Haigh and List 2005), coordination between people (Cachon and Camerer 1996); choice bracketing (Read, et al. 1999; Rabin and Weidsacker 2009); housing market selling patterns due to loss aversion (Genesove and Mayer 2001; Einio, et al. 2008); and consumption behavior (Bowman, et al. 1999; Heidhues and Koszegi 2009; Samuelson and Zeckhauser 1988; Johnson and Goldstein 2003). Daniel Kahneman, a 2002 Nobel laureate in Economics, supports the statement that "the notion of loss aversion is unquestionably the most important contribution of psychology to behavioral economics.". Starmer (2000) gives an overview of the theoretical interpretations, whereas Camerer (2004) provides a description of the field findings. According to current studies and the importance of loss aversion for investors and human behavior, I hypothesize the following:

**Hypothesis 2:** Crypto investors present lower loss aversion than general population.

### 3.3. Risk attitudes in existing literature

Pezzani (2018) noted that Bitcoin investors' erroneous views regarding the cryptocurrency's everlasting rise have caused them to overvalue the margin earned through speculating. In line with sensation-seeking, risk propensity is an investor's inclination to risk more during periods of high volatility because he or she finds trading enjoyable and stimulating (Mai, 2019). A risk-seeking investor would find Bitcoin investment more exciting due to its fast-paced, diverse environment (Mai, 2019). Numerous research papers support the notion that risk preferences are central to financial decision-making (Nosi and Weber, 2010; Weber et al., 2013), and a growing review of the literature dating all the way back to Leland (1968) suggests that higher order risk preferences may be more relevant for explaining certain behaviours, such as health-related behaviour and financial decision-making, than risk aversion (Courbage and Rey, 2006; Kimball, 1990, 1992; Attema et al., 2019; Gollier and Pratt, 1996). Individuals' levels of prudence and temperance have implications for a wide variety of economic activities, including bargaining (White 2008), bidding in auctions (Eso and White 2004), the valuation of medical treatments (Bleichrodt 2003) sustainable development (Gollier 2011), tax compliance (Snow and Warren 2005; Alm 1988). In addition to the above, Chelly Arcibal of the South China Morning Post believes that crypto investors are more risk averse than the ordinary rich individual. Individual risk attitudes have been researched extensively during the past decade. However, the majority of research has been on the investigation of risk aversion (Pratt, 1964; Richard, 1975) and its impact on individual decision making, as reflected in economic and financial decisions (Sapienza et al., 2009; Cohn et al., 2015). Recently, higher order risk attitudes, including prudence and temperance, have been studied (for a review, see Trautmann and van de Kuilen, 2018). In a framework of anticipated utility, prudence is connected to the convexity of the first derivative of the utility function, which is equal to a third derivative that is greater than zero ($u''' > 0$; Kimball, 1990). In a similar fashion, moderation is associated with the concavity of the second derivative of the utility function, which is comparable to a negative fourth derivative (u"" 0; Kimball, 1993).

Prudence is defined by an aversion to downside risks (Eeckhoudt, Gollier, and Schneider, 1995; Eeckhoudt and Schlesinger, 2006), meaning that people who are prudent prefer to connect risk with good world states or when wealth is greater. In addition, prudence may be seen as a preference for skewness (Ebert, 2013), a key notion in finance (Harvey and Siddique 2000; De Roon and Karehnke 2017), and for bigger savings (Leland, 1968; Kimball 1992). Ackert et al. (2006) and Huber et al. (2014) observed higher pricing for positively skewed assets relative to negatively skewed and non-skewed assets in an experimental asset market where this preference might be linked to trading behavior. In addition, Huber et al. (2014) notes that this overpricing disappeared when respondents were not informed of the probabilities and payoffs of each asset. However, these findings must be weighed against a recent and comprehensive analysis by Huber et al. (2017), who demonstrates that skewness is not a significant determinant in traders' risk perception and asset prices. Consequently, trader prudence and asset return skewness are current themes requiring more research to better comprehend market dynamics.

Temperance is a tendency for disaggregating two distinct problems rather than combining them (Eeckhoudt and Schlesinger, 2006). It has been emphasized that temperance may be viewed as an aversion to kurtosis (Ebert, 2013), which is crucial for the valuation of assets in finance (Corrado and Su 1996; Harvey and Siddique 2000). Using an experimental methodology, Noussair et al. (2014) finds that moderation decreases the likelihood of a subject having hazardous investments and the proportion of risky assets in an asset portfolio.

As prudence and temperance are connected to financial decisions, it is vital to examine and measure these attitudes among the participants. This is precisely what is presented in this study by studying the higher order risk attitudes of cryptocurrency investors. In line with the theoretical work of Eeckhoudt and Schlesinger (2006), which ties higher order risk ideas to preferences in lottery decisions, Noussair et al. (2014) conducted an experiment with a large sample of 3,566 respondents (3547 dutch individuals and 109 students). They were able to evaluate these risk attitudes, examine their associations with risk aversion, relate them to demographic data, and investigate their consequences for savings and portfolio decisions by presenting a variety of treatments with variable payoffs, profits, and risks. The third hypothesis emerges naturally from the literature:

**Hypothesis 3:** Crypto investors present greater tolerance to risk exposure than general population.

### 3.4. Personality Traits

Numerous studies have been conducted to determine the influence of personality traits on investment decisions, economic preferences and other factors at the individual and household level, including decisions regarding debt acquisition and the holding of financial assets. This thesis includes a selection of research that have studied the relationships between the big five personality traits and other variables, with a focus on the risk-taking profiles of individuals.

For instance, in two papers, Kirchler et al. (2018) and Kirchler et al. (2020) report that finance professionals are more competitive than students, academics, and the general population, but less competitive than professional athletes. It is demonstrated that perceived competitiveness is associated with greater degrees of psychopathy (Spurk and Hirschi, 2018; Jonason, 2015). Psychopathy is especially relevant to financial decision-making because it explains deviant conduct such as taking risks on behalf of others and gambling with other people's money (Jones, 2014; Jones, 2013). Furthermore, associations between low neuroticism and high openness from Big-5 personality traits and risk taking are exhibit (Lauriola and Levin, 2001). Using data from one wave of the British Household Panel Survey, Brown and Taylor (2014) find that certain Big Five personality traits (namely Conscientiousness, Extraversion, and Agreeableness) correlate with the level of unsecured debt and savings. They also investigate the association between the Big Five personality traits and the ownership of assets, finding substantial negative correlations only between stock ownership and extraversion and agreeableness. Bucciol et al. (2015) note that personality traits influence one's perceived position in the social hierarchy, and Zarri (2017) demonstrates that agreeableness is negatively associated with stock ownership too.

In a 2018 study based on the Big Five Personality Model, Sreedevi and Chitra examined the impact of emotional stability, return, extraversion, risk, agreeableness, conscientiousness, and reasoning on investment decisions. Their findings demonstrate that personality has an effect on decision-making and on investing technique selection.

Specifically, in regard to risk preference, (Mayfield, Perdue, and Wooten, 2008; Rustichini, De Young, Anderson, and Burks, 2012; Nicholson, Fenton, Soane, and Willman, 2002) all investigated the influence of personal characteristics. Mayfield, Perdue, and Wooten attempted to discover the methods in which investors' personal qualities influence their perceptions of risk. Extroverts tend to choose short-term investments, whilst individuals with a high level of openness to experience favor longer-term investments. People with a high neuroticism score are hesitant to invest in the short term. The link between the trait of openness to experience and risk aversion are shown to be statistically significant and negative. The extraversion attribute is inversely associated with the prevention of investment risk. The traits of extraversion and conscientiousness are positively connected to short-term investment (Mayfield, Perdue and Wooten, 2008). Similar findings were made by Nicholson, Fenton, Soane, and Willman in 2002, who discovered that risk propensity was associated with high scores for extraversion and openness to experience and low scores for neuroticism, agreeableness, and conscientiousness.

Almlund, Duckworth, Heckman, and Kautz (2011), who explore the role of personality traits as both predictors and causes of economic outcomes in a recent comprehensive survey on personality psychology and economics, interpret measured personality as a construct derived from an economic model comprising preferences, constraints, and information. They explore how the five factor theory in personality psychology focuses on the importance of personality traits in determining outcomes and the actions performed by agents, resulting in a dynamic information set as individuals learn about their qualities. In addition, they examine the limited but expanding literature linking preferences and personality, including the association between risk aversion and openness to experience (see, for example, Dohmen, Falk, Human, and Sunde, 2012) and the connection between risk aversion and neuroticism (see, for example, Borghans, Duckworth, Heckman, & ter Weel, 2008). In the management and psychology literature, the so-called "Big Five" model is one of the most often employed taxonomies (Costa and McCrae, 1992). This model encompasses a vast array of personality traits (Lonnqvist et al., 2015), and it posits that five traits are fundamental and universal, and that a person's score on these dimensions characterizes her stable pattern of thoughts and emotions (Rustichini et al., 2012). The Big Five model gives a comprehensive classification of personality traits that also includes increasingly finely defined features at progressively lower levels (Almlund et al., 2011). Nyhus and Webley (2001) find that those with greater emotional stability and introversion save more and borrow less, whereas individuals with greater agreeableness do the opposite. A number of publications examine the correlation between the Big Five qualities and incomes (see, e.g., Mueller and Plug, 2006). Rustichini et al. (2012) demonstrate that personality variables influence a variety of economic and life outcomes, including credit score, job persistence, heavy truck accidents, and smoking habit, with personality traits possessing a higher predictive power than economic preferences. Becker et al. (2012) evaluate the explanatory power of economic preferences and personality measures in accounting for health, educational, and labor market outcomes and conclude that standard measures of preferences and personality are complimentary constructs. The empirical analysis of Letkiewicz and Fox (2014) suggests that conscientiousness predicts asset accumulation among young Americans. In addition to cynical hostility, anxiety, and rage, relevant personality qualities also include cynical hostility. Despite popular interest in the subject of whether cryptocurrency investors differ systematically from other types of investors or the broader population, few scientific research examine certain personality traits of cryptocurrency practitioners.

## 4. Experiments and variables

I conducted the experiment using the online survey tool Qualtrics. Qualtrics is an online survey platform that enables students, researchers, and other individuals to create complex surveys for a variety of purposes under privacy and security. Surveys were delivered via social media platforms from May 19 to June 13, 2022, specifically Telegram, LinkedIn, and Survey Circle. The initial sample size was 209 individuals, however only 163 completed the survey to achieve a 78 percent level of completeness. In order to prevent missing data, uncompleted questionnaires are not included in the final sample for experimentation. Due to the inclusion criterion that respondents, be at least 18 years old, nonprobability sampling was more efficient and cost-effective. (Bhat, 2019). Participation in the study was restricted to those individuals who, after reading the terms, freely and unambiguously consented to complete the survey. After accepting their participation, respondents were questioned about their demographic profiles, economic preferences and personal traits. As respondents choose whether or not to participate, the minimal number of undecided respondents enhanced the quality of the collected data. People were invited to distribute the questionnaire using the snowball sampling method. This technique has the ability to incorporate individuals from the same social network in the sample. This may have reduced the sample's representativeness and generalizability to the entire population. Using econometric methods such as nonparametric tests of hypothesis and Probit model regression to assess the answers, the study was quantitative in nature. Each of the five components of this experiment is addressed separately and last approximately 10 minutes in total. Specifically, each subsection gives a succinct justification for the thesis's objectives, a detailed explanation of the experimental implementation, a discussion of my addition to the prior literature, and a summary of the key findings associated with the specific component of this thesis. The following is a brief description of the utilized variables:

## 5. Variables

### 5.1.Demographic- socioeconomic statistics

Demographic and socioeconomic data are used to gain a deeper knowledge of the background characteristics of respondents. Age, gender, relationship status, income, job position, and level of education identified as factors which affect stock investors hence it could be the same for cryptocurrencies. By include demographic questions in survey, it is possible to collect a vast amount of demographic data on existing and prospective customers, which may be utilized to design a market segmentation strategy for targeting the appropriate clients. (Noussair, 2014).

***Method.*** Participants were asked to answer a series of questions according their demographic and socioeconomic statistics. I follow the existing literature (Hong et al., 2004; Lee et al., 2010; Conlin et al., 2015; Ahmad, 2017; Tauni et al., 2017; Oehler et al., 2018; Kim, Hong, Hwang, Kim and Han, 2020) in order to collect most appropriate demographic info that affects investors behavior.

### 5.2. Present bias

In economics, time preference refers to the present relative value put on obtaining an item or some cash sooner rather than later. The discount function mathematically captures time preferences. The greater the temporal preference, the greater the discount applied to future receivables or expenses due (Irving Fisher).

***Method.*** Participants were asked to make a series of judgments involving a trade-off between a lesser amount paid on an earlier date and a bigger amount paid on a later date in order to determine their time preferences. In the experiment, a Multiple Price List (MPL) was utilized to induce a degree of patience. Participants made 11 decisions between an earlier and a later payout (Table 1). In each question, participants were asked to choose between receiving a payment today or larger payments in 12 months. The payout for the immediate payment (option A) was 100 and remained constant in all subsequent questions, whereas the payout for the delayed payment (option B) began at 100 and increased by 10 increments until it reached 200 after 12 months. My proxy for patience is the moment at which we transition from Option A to Option B, with earlier shifts being linked with greater degrees of patience. In the survey, I used a quantitative measure developed by Falk et al. (2016) and Falk et al. (2018) consisting of a series of eleven interdependent hypothetical binary choices between immediate and delayed financial rewards, in a format commonly referred to as the "staircase" (or "unfolding brackets") procedure (Cornsweet, 1962). The staircase measure is based on the same fundamental concept as the Multiple Price List, but it reduces the amount of questions asked of participants. The questions "zoom in" on the respondent's point of indifference between the smaller immediate payment and the bigger delayed payment by altering the delayed payment based on their prior responses. The sequence of questions has 11 different ordered outcomes, allowing us to create a measure of patience ranging from 1 to 11 - where 11 represents the lowest amount of patience and 1 the most.

*Table 1. Decisions between an earlier and a later*

| Decision | Option A | Option B | Switch to option B | Patience proxy |
|---|---|---|---|---|
| 1 | 100 | 100 | 1 | 1 |
| 2 | 100 | 110 | 2 | 2 |
| 3 | 100 | 120 | 3 | 3 |
| 4 | 100 | 130 | 4 | 4 |
| 5 | 100 | 140 | 5 | 5 |
| 6 | 100 | 150 | 6 | 6 |
| 7 | 100 | 160 | 7 | 7 |
| 8 | 100 | 170 | 8 | 8 |
| 9 | 100 | 180 | 9 | 9 |
| 10 | 100 | 190 | 10 | 10 |
| 11 | 100 | 200 | 11 | 11 |

### 5.3. Loss aversion

The propensity to prioritize avoiding losses over earning comparable benefits is referred to as loss aversion. The idea is well-known in economics. What separates loss aversion from risk aversion is that the value of a monetary payout is contingent upon prior experiences or expectations. According to some research, losses are twice as potent psychologically as profits. Amos Tversky and Daniel Kahneman were the first to identify loss aversion (Simon Gächter, 2007).

***Method***. The third objective is to quantify loss aversion in risk decisions. This is accomplished by adapting a simple lottery choice problem from Fehr and Goette (2007), which may also evaluate loss aversion. In this choice assignment, participants determine for each of six lotteries whether or not to accept (i.e., play) it (and receive nothing). In each lottery, the winning number is always 6, but the losing number varies (between 2 and 7). Table 2 depicts the decision sheet provided to subjects during the lottery choice test. This task evaluates loss aversion rather than risk aversion, as suggested by Rabin (2000), Rabin and Thaler (2001), Schmidt and Zank (2005), Wakker (2005), Kobberling and Wakker (2005), Fehr and Goette (2007). Rabin (2000), for example, argues that risk aversion cannot convincingly explain decision behavior in low-stakes dangerous situations such as ours. Risk aversion (i.e., a concave utility of wealth function) in such low-stakes lotteries would suggest ridiculous levels of risk aversion in high-stakes wagers. Therefore, according to Rabin (2000), individuals participating in such wagers should be risk neutral under EU law. Therefore, in my choice problem, individuals should select lotteries 1 through 6, which all have positive anticipated values. If, despite this, I witness rejections of low-stakes wagers with a positive anticipated value, this may indicate loss aversion as opposed to risk aversion. Utilizing cumulative prospect theory, loss aversion can be determined by the choice problem (Tversky and Kahneman 1992). w+(0.5)v(G) = w–(0.5)risky(L), where L is the loss in a specific lottery and G is the gain; v(x) is the utility of the outcome x G, L; risky represents the coefficient of loss aversion in the risky choice task; and probability weights are been presented by w+(0.5) and w–(0.5) for a 50 percent chance of gaining as Perlec (1998) present. A common assumption for v(x) is that it is linear (v(x) = x) for small quantities, which gives us a fairly straightforward measure of loss aversion: risky = G/L. I eventually modify some of these assumptions. The sequence of questions has 6 different ordered outcomes, allowing us to create a measure of loss aversion ranging from 1 to 6- where 6 represents the lowest amount of loss aversion and 1 the most (Table 2).

*Table 2. The lottery choice task*

| Lottery | | Accept | Reject |
|---|---|---|---|
| #1 | If the coin turns up heads, then you lose 2€; if the coin turns tails, you win 6€ | | |
| #2 | If the coin turns up heads, then you lose 3€; if the coin turns tails, you win 6€ | | |
| #3 | If the coin turns up heads, then you lose 4€; if the coin turns tails, you win 6€ | | |
| #4 | If the coin turns up heads, then you lose 5€; if the coin turns tails, you win 6€ | | |
| #5 | If the coin turns up heads, then you lose 6€; if the coin turns tails, you win 6€ | | |
| #6 | If the coin turns up heads, then you lose 7€; if the coin turns tails, you win 6€ | | |

**5.4. Risk attitudes**

In economics and finance, risk preference refers to people's propensity to favour outcomes with low uncertainty over those with high uncertainty, even when the average value of the latter is equal to or greater than the more certain result. Risk preference accounts for the proclivity to consent to a circumstance with a more predictable but maybe lower payout over another with a more uncertain but possibly greater payoff (Fenghua Wen, 2014).

***Method***. To elicit prudence, risk aversion and temperance, I replicate the experimental technique given by Noussair et al. (2014), who based their experiment on Eeckhoudt and Schlesinger's theoretical framework (2006). Participants are presented with 15 binary options amongst lotteries in succession. These options are separated into three categories. The first section consists of five options between a guaranteed payment and a lottery with two payoffs that have equal odds. Part two of the prudence exam consists of five binary choices between two distinct lotteries and part three of the temperance exam consists of five binary choices between two distinct lotteries. Table 4 presents an overview of the 15 binary choices in succession. [a b] symbolizes a lottery with equal odds.

Like in Noussair et al. (2014), I quantify an individual's risk aversion by the number of safe options he made out of five decisions involving a certain payment and a risk lottery (choices 1 to 5 in Table 3). I asses prudence as the number of prudent choices made in the five scenarios of table 3 (choices 6 to 10 in Table 3) and measure temperance as the amount of temperate choices made in the five situations of Table 3 (choices 11 to 15 in Table 3).

*Table 3. List of choice tasks (table of Noussair et al., 2014)*

| | **Left lottery** | **Right lottery** |
|---|---|---|
| **Risk_av 1** | 20 | 65 or 5 |
| **Risk_av 2** | 25 | 65 or 5 |
| **Risk_av 3** | 30 | 65 or 5 |
| **Risk_av 4** | 35 | 65 or 5 |
| **Risk_av 5** | 40 | 65 or 5 |
| **Prub 1** | 90 + [20, -20], 60 | 90, 60+ [20, -20] |
| **Prub 2** | 90 + [10, -10], 60 | 90, 60+ [10, -10] |
| **Prub 3** | 90 + [40, -40], 60 | 90, 60+ [40, -40] |
| **Prub 4** | 135 + [30, -30], 90 | 135, 90+ [30, -30] |
| **Prub 5** | 65 + [20, -20], 35 | 65, 35+ [20, -20] |
| **Temp 1** | 90+ [ 30, -30], 90+ [30, -30] | 90, 90+ [30, -30] + [30, -30] |
| **Temp 2** | 90+ [ 30, -30], 90+ [10, -10] | 90, 90+ [30, -30] + [10, -10] |
| **Temp 3** | 90+ [ 30, -30], 90+ [50, -50] | 90, 90+ [30, -30] + [50, -50] |
| **Temp 4** | 30+ [ 10, -10], 30+ [10, -10] | 30, 30+ [10, -10] + [10, -10] |
| **Temp 5** | 70+ [ 30, -30], 70+ [30, -30] | 70, 70+ [30, -30] + [30, -30] |

*a_b indicates an equiprobable lottery to receive either a or b; choice of the left lottery indicates risk aversion, prudence and temperance.*

### 5.5. Personal traits

As the scrutiny of cryptocurrency investors has increased, the psychological traits of cryptocurrency investors should be extensively examined. As personal characteristics are an elusive notion, we restrict our research to traits that are frequently the subject of public debate: the habitual patterns of personality traits (Zillig et al., 2002).

***Method.*** To address this variable, I examine the personal traits based on the Big Five method using the validated 10-item assessment developed by Oliver and Rammstedt (2007). Individuals are asked to rate themselves on a five-point scale from 'I totally disagree', which takes the value of 1, to 'I totally agree', which takes the value of 5, according to two statements relating to each of the five personality factors. Hence, there are 10 questions in total, which are detailed in the table 4 below.

*Table 4. Personal traits according to big 5*

| Traits | Statements |
|---|---|
| **Extroversion** | |
| (+) | I see myself as someone who is outgoing and sociable |
| (-) | I see myself as someone who is reserved |
| **Agreeableness** | |
| (+) | I see myself as someone who is generally trusting |
| (-) | I see myself as someone who tends to find fault with others |
| **Conscientiousness** | |
| (+) | I see myself as someone who does a thorough job |
| (-) | I see myself as someone who tends to be lazy |
| **Neuroticism** | |
| (+) | I see myself as someone who gets nervous easily |
| (-) | I see myself as someone who is relaxed and handles stress well |
| **Openness** | |
| (+) | I see myself as someone who has an active imagination |
| (-) | I see myself as someone who has few artistic interests |

*Table 5. Variables of thesis*

| Variable name | Description |
|---|---|
| **Dependent variable** | |
| D_CryptoInvestor | Dummy variable equal 1 if cryptocurrency investor |
| **Control variables** | |
| Male | Dummy variable equal 1 if male participant |
| Age | Categorical Age-related classifications |
| Relationship | Categorical regarding relationship status |
| Education | Categorical regarding level of education |
| Income | Categorical regarding level of income |
| Job | Categorical regarding employment standing |
| **Independent** | |
| Presentbias | Economic preference evaluation of present biases |
| Lossav | Economic preference evaluation of loss aversion |
| Riskav | Economic preference evaluation of risk aversion |
| Prud | Economic preference evaluation of prudence |
| Temp | Economic preference evaluation of temperance |
| Extroversion | Personality trait measuring extroversion |
| Agreeableness | Personality trait measuring agreeableness |
| Conscientiousness | Personality trait measuring conscientiousness |
| Neuroticism | Personality trait measuring neuroticism |
| Openness | Personality trait measuring openness |

# 6. Results

## 6.1. Summary statistics

Table 6 provides a summary of the most important statistics. Even if respondents are divided into two basic categories cryptocurrency investors and non-cryptocurrency investors, it would be more appropriate to divide non-cryptocurrency investors into stock market investors and the general population based on their investments or lack of intent to invest in the near future, as indicated at the beginning of the survey. This separation allows me to see each category more clearly hence that I can make the appropriate comparisons. In contrast to the general population, which is dominated by females, the sample of cryptocurrency and stock market investors is over two-thirds male. The average age of investors in both groups is roughly the same, whereas the general population is 3 years older. On the one hand, relationship status and education levels are similar across all categories, so the majority of participants hold at least a bachelor's degree or its equivalent and are unmarried, but on the other hand, stock investors have a higher income than the other two groups. In addition, the majority of participants in all categories hold part-time employment and exhibit a low level of present bias on a scale ranging from 0 to 11, as well as average levels of prudence, loss aversion, and risk aversion. Last but not least, the participants of all groups demonstrates positive results for all personality traits, with the exception of neuroticism, for which investors and the general population demonstrate negative results.

*Table 6. Summary statistics of Cryptocurrency, Stock investors and General population*

| | Cryptocurrency investors I | | Stock investors II | | General population III | | II-I | III-I |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD.** | | |
| **Male** | 0,730 | 0,520 | 0,783 | 0,500 | 0,400 | 0,112 | 0,529 | -0,330*** |
| **Age** | 26,939 | 0,588 | 27,246 | 0,638 | 30,300 | 2,037 | 0,307 | 3,361** |
| **Relationship** | 1,338 | 0,476 | 1,348 | 0,564 | 1,400 | 0,503 | 0,010 | 0,062 |
| **Education** | 5,541 | 0,666 | 5,493 | 0,633 | 5,350 | 0,745 | -0,048 | -0,191 |
| **Income** | 1,500 | 0,798 | 1,899 | 0,987 | 1,500 | 0,761 | 0,399*** | 0,000 |
| **Job** | 2,081 | 1,132 | 2,449 | 1,078 | 2,250 | 1,070 | 0,368** | 0,169 |
| **Presentbias** | 2,568 | 3,088 | 2,580 | 3,487 | 4,000 | 4,377 | 0,012 | 1,432 |
| **Lossav** | 2,419 | 1,383 | 2,681 | 1,558 | 1,600 | 1,353 | 0,424 | -0,819* |
| **Riskav** | 2,770 | 1,200 | 2,275 | 1,688 | 2,200 | 1,852 | -0,495** | -0,570 |
| **Prud** | 2,081 | 1,789 | 1,667 | 1,729 | 1,800 | 1,642 | -0,414 | -0,281 |
| **Temp** | 3,203 | 1,663 | 2,087 | 1,805 | 2,200 | 1,609 | -1,116*** | -1,003** |
| **Extroversion** | 0,676 | 1,325 | 0,812 | 1,726 | 1,200 | 1,281 | 0,136 | 0,524 |
| **Agreeableness** | 1,311 | 1,470 | 1,014 | 1,500 | 1,150 | 1,348 | -0,296 | -0,161 |
| **Conscientiousness** | 0,851 | 1,468 | 1,072 | 1,965 | 0,500 | 1,732 | 0,221 | -0,351 |
| **Neuroticism** | -0,068 | 2,002 | -1,116 | 2,272 | -0,45 | 1,099 | -1,048*** | -0,382 |
| **Openness** | 1,257 | 1,553 | 0,652 | 1,359 | 0,500 | 1,147 | -0,605** | -0,757** |
| **Observations** | 74 | | 69 | | 20 | | | |

****, **, * indicates significance at the 1%, 5% and 10% level*

### 6.2. Raw differences

To identify raw differences between cryptocurrency and cryptocurrency investors, a non-parametric test of the null hypothesis must be conducted. The Mann-Whitney test is a nonparametric test of the null hypothesis that, for randomly selected values X and Y from two data sets, the probability that X is greater than Y equals the probability that Y is greater than X. I am implementing the concept of group separation in summary statistics to gain a better understanding of the differences between each group. The majority of variables for the MWW test between stock and cryptocurrency investors (table 7) are different, but only six of them are statistically significant. There are significant 1 percent differences in income (p= 0.0073), temperance (p=0.0003), and neuroticism (p=0.0054) between investors in stocks and cryptocurrencies. In the second MWW test (table 7) for crypto investors and the general population, there are fewer significant raw differences. Gender is the statistically significant difference with a p-value of 0.006, while the rest are at the 0.05 level.

*Table 7. Mann-Whitney-Wilcoxon test between Stock investors– Cryptocurrency investors and General population- Cryptocurrency investors*

| | **MWW test** | | | |
|---|---|---|---|---|
| | **Stock investors- Crypto investors** | | **General population- Crypto investors** | |
| | **I** | **II** | **I** | **II** |
| | **z-score** | **p- value** | **z-score** | **p- value** |
| **Male** | 0.732 | 0.4640 | -2.746*** | 0.0060 |
| **Age** | 0.287 | 0.7745 | 1.513 | 0.1303 |
| **Relationship status** | -0.178 | 0.8584 | 0.514 | 0.6072 |
| **Education** | -0.636 | 0.5248 | -1.121 | 0.2622 |
| **Income** | 2.685*** | 0.0073 | 0.179 | 0.8580 |
| **Job** | 2.014** | 0.0440 | 0.648 | 0.5171 |
| **Present bias** | 0.046 | 0.9632 | 1.019 | 0.3083 |
| **Lossav** | 1.488 | 0.1374 | -2.313** | 0.0207 |
| **Riskav** | -1,712* | 0.0870 | -1.132 | 0.2577 |
| **Prud** | -1.535 | 0.1247 | -0.556 | 0.5785 |
| **Temp** | -3.167*** | 0.0003 | -2.351** | 0.0187 |
| **Extroversion** | 0.638 | 0.5237 | 1.575 | 0.1153 |
| **Agreeableness** | -1.314 | 0.1889 | -0.832 | 0.4056 |
| **Conscientiousness** | 1.053 | 0.2923 | -0.958 | 0.3382 |
| **Neuroticism** | -2.780*** | 0.0054 | -0.908 | 0.3637 |
| **Openness** | -2.310** | 0.0209 | -2.366** | 0.0180 |

***, **, * indicates significance at the 1%, 5% and 10% level

### 6.3. Correlations

The Spearman correlation matrix for all variables is depicted in Table 6 by the number 0 to 1. The closer the value is to 1 the greater the correlation between the variables, and vice versa. As the correlation coefficient between independent variables are no more than 0.80 and most coefficients are statistically insignificant, the correlation matrix in Table 6 rules out multicollinearity. When there is significant multicollinearity in the regression, the R-squared coefficient may be high and the regression may be statistically significant; however, the t-test of each parameter is not statistically significant, resulting in a different symbol for the regression coefficient and an utterly untrue conclusion. Regarding the Spearman correlation, Table 8 demonstrates that my dependent variable D_CryptoInvestor is positively correlated with the majority of variables, with the exception of age, income, present bias, extroversion, and conscientiousness. The greatest significant correlation of dependent variable exists between temperance, openness, and neuroticism, with 30 percent, 22 percent, and 21 percent, respectively, at the level of 0.01. The majority of control variables, namely Male, Age, Education, and Income, are significantly negatively correlated with Neuroticism and Openness. The fact that the variables of high order risk attitudes (Riskav, Temp, and Purd) are significant at the level of 0.01 is one of the most remarkable results of this correlation; specifically, Riskav and Prud have the second highest correlation between all variables in the table. This result is consistent with Noussair et al. (2014), who found significant correlations between three variables and a correlation between education and risk aversion. Another finding supported by prior research by Lauriola and Levin (2001) is the association between neuroticism, openness, and risk aversion. In contrast to the findings of Bucciol et al. (2015) and Zarri (2017), which indicate that agreeableness is negatively associated with stock ownership, my results reveal a positive correlation of 11 percent, albeit at an insignificant level. Male participants have a positive correlation with cryptocurrency investors, consistent of my results and Hasso et al. (2019), but not to a significant degree.

*Table 8. Spearman correlation for Crypto vs non Crypo investors and p-values*

| | D_Crypto | Male | Age | Education | Income | Present bias | Lossav | Riskav | Prud. | Temp. | Extr. | Agreeabl. | Consc. | Neur. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| D_CryptoInvestor | | | | | | | | | | | | | | |
| | 1 | | | | | | | | | | | | | |
| Male | 0.0364 | 1 | | | | | | | | | | | | |
| | (0.6448) | | | | | | | | | | | | | |
| Age | -0.0618 | 0.5069*** | 1 | | | | | | | | | | | |
| | (0.4332) | (0.0000) | | | | | | | | | | | | |
| Education | 0.0725 | -0.0596 | 0.0378 | 1 | | | | | | | | | | |
| | (0.3575) | (0.4496) | (0.6320) | | | | | | | | | | | |
| Income | -0.1797** | 0.1436** | 0.3301*** | 0.0631 | 1 | | | | | | | | | |
| | (0.0217) | (0.0674) | (0.001) | (0.4235) | | | | | | | | | | |
| Present bias | -0.0317 | 0.1941** | 0.1708** | -0.0182 | -0.0491 | 1 | | | | | | | | |
| | (0.6875) | (0.0130) | (0.0293 ) | (0.8177) | (0.5339) | | | | | | | | | |
| Lossav | 0.0074 | 0.1765** | -0.0301 | 0.0778 | -0.0214 | -0.0193 | 1 | | | | | | | |
| | (0.9256) | (0.0242) | (0.7028) | (0.3235) | (0.7864) | (0.8069 ) | | | | | | | | |
| Riskav | 0.1423* | -0.0599 | -0.1105 | 0.1809** | 0.0599 | -0.1456* | 0.1956** | 1 | | | | | | |
| | (0.0700) | (0.4478) | (0.1602) | (0.0209) | (0.4478) | (0.0637) | (0.0124 ) | | | | | | | |
| Prud. | 0.1153 | -0.0433 | 0.0669 | 0.1598** | 0.0697 | -0.0941 | 0.0912 | 0.3824*** | 1 | | | | | |
| | (0.1428) | (0.5830) | (0.3960) | (0.0416) | (0.3769) | (0.2319) | (0.2471) | (0.0000 ) | | | | | | |
| Temp. | 0.3003*** | 0.0895 | -0.0219 | 0.1173 | -0.0888 | -0.0705 | 0.1960** | 0.2475*** | 0.4196*** | 1 | | | | |
| | (0.0001) | (0.2559) | (0.7811) | (0.1359) | (0.2594) | (0.3715) | (0.0122) | (0.0014) | (0.0000) | | | | | |
| Extroversion | -0.0856 | -0.2281*** | -0.1988** | 0.1896** | 0.1219 | 0.1032 | -0.0522 | 0.1005 | -0.0549 | 0.0079 | 1 | | | |
| | (0.2770) | (0.0034) | (0.0110) | (0.0154) | (0.1212) | (0.1899) | (0.5082) | (0.2018) | (0.4864) | (0.9198) | | | | |
| Agreeableness | 0.1087 | 0.0220 | -0.0362 | 0.1729** | -0.1524* | -0.0959 | 0.1072 | 0.0877 | 0.0358 | 0.1574** | 0.0654 | 1 | | |
| | (0.1672) | (0.7800) | (0.6464) | (0.0273) | (0.0521) | (0.2231) | (0.1732) | (0.2656) | (0.6498) | (0.0448) | (0.4067) | | | |
| Conscientiousnes | -0.0413 | -0.0518 | -0.1273 | 0.2835*** | 0.2060*** | 0.0294 | -0.1346* | 0.0843 | 0.1242 | -0.0132 | 0.2442*** | 0.0227 | 1 | |
| | (0.6008) | (0.5113) | (0.1052) | (0.0002) | (0.0083) | (0.7093) | (0.0867) | (0.2849) | (0.1143) | (0.8668) | (0.0017) | (0.7732) | | |
| Neuroticism | 0.2060*** | -0.3326*** | -0.2787*** | 0.0823 | -0.2227*** | -0.0477 | -0.1374* | -0.0650 | 0.1643** | 0.0349 | -0.0949 | -0.0875 | -0.1241 | 1 |
| | (0.0083) | (0.0000) | (0.0003) | (0.2964) | (0.0043) | (0.5454) | (0.0803) | (0.4100) | (0.0361) | (0.6580) | (0.2281) | (0.2666) | (0.1145) | |
| Openness | 0.2172*** | -0.2219*** | -0.0904 | 0.1597 | -0.0019 | -0.2086*** | 0.1902** | 0.2007** | 0.1586** | 0.2090*** | 0.1827** | 0.1161 | -0.0846 | 0.1820** |
| | (0.0054) | (0.0044) | (0.2511) | (0.0417) | (0.9804) | (0.0075) | (0.0150) | (0.0102) | (0.0432) | (0.0074) | (0.0196) | (0.1399) | (0.2832) | (0.0201) |

The *p*-values are in parenthesis
* significant at 10%; ** significant at 5%; *** significant at 1%.

### 6.4. Regression analyses

I perform logistic regressions using a dummy for participation as the dependent variable. Participation is defined as cryptocurrency or stock investors for the first model result and as cryptocurrency investors or the general population for the second. Individual personality trait scores are represented by five different categorical variables, and each economic preference has its own categorical variable. The basic form of the regressions is:

$$D\_CryptoInvestor_i = \beta 1 Male_i + \beta 2 Age_i + \beta 3 Education_i + \beta 4 Income_i + \beta 5 Present\ bias_i + \beta 6 Lossav_i + \beta 7 Riskav_i + \beta 8 Prud_i + \beta 9 Temp_i + \beta 10 Extroversion_i + \beta 11 Agreeableness_i + \beta 12 Conscientiousness_i + \beta 13\ Neuroticism_i + \beta 14\ Openness_i + u_i$$

As controls, I include age, level of education, income, a dummy variable for gender, employment, and relationship status. Both regressions, adhere to the same research methodology. To be more specific, due to the fact that additional insights are gained as more regressions are performed, each of them consists of six different models. I report the regression coefficients, robust standard errors and the marginal effect for each individual as, in Greene (2008, p.775). Tables 9 and 10 report the results for regressions, model 1 contains only the economic preferences (present bias, loss aversion, risk aversion, temperance and prudence).

Model 2 adds all the control variables, then model 3 includes all independent variables and after that, different combinations investigated. In the fourth model, I eliminate the control variables in order to examine empirical evidence between economic preferences and personality traits with greater clarity, same way model 5 include controls and personal traits. Last model 6 consists only of personal traits. The only difference between regression models is the dummy-dependent variable, which is equal to 1 for cryptocurrency investors and 0 for stock market investors in the first hypothesis, while in the second and third hypothesis regression, the 0 value of the dummy variable is equivalent to the general population.

### 6.5. Regression for Hypothesis 1

H1: Crypto investors have longer term preferences than stock investors.

The results of the first regression (table 9) indicate that the present bias shifts when variables are added or subtracted from a model. In the first model, where each variable is set to its sample average, 1 unit of present bias is estimated to decrease the probability of being a crypto investor as opposed to an equity investor by 0.009 percentage points. This result suggests that as participants' present bias increased, so did their impatience, and crypto investors are more likely to be impatient than stock market investors. Across all models, values vary , whether they have a positive or negative effect, but none of these values were statistically significant. The statistical evidence that stock market investors are less loss averse than cryptocurrency investors in every model with 5% statistical significance is one of the most remarkable results that no existing literature covers. Moreover, investors in the stock market are less risk averse in every model, particularly model three in which all variables have a statistical significance of 10%. Control variables reveal a number of intriguing facts, such as the fact that women, elderly, married individuals with lower levels of education and income are more likely to invest in cryptocurrencies. One unit of unemployment is estimated to increase the likelihood of being a crypto investor rather than a stock investor by 0.1725 percentage points in Model 3 and 0.1985 percentage points in Model 4, both statistically significant at the 10% level in Models 3 and 4. The table provides evidence that an increase in neuroticism has a negative relationship with stock market participation; this relationship remains statistically significant at 5% across all three models. An increase in openness is also positively associated with cryptocurrency investors, but only at a significance level of 10% when personal characteristics are studied in isolation from other variables. Agreeableness is positively correlated with cryptocurrency while extroversion is negatively correlated, but neither of these relationships is statistically significant. Last but not least, conscientiousness is positively associated with stock investors because it remains statistically significant across all four models, albeit at a low level: it is estimated that 1 unit of conscientiousness reduces the likelihood of being a crypto investor rather than a stock investor by 0.0053 percentage points.

*Table 9. Regression for 1st hypothesis*

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | | Model 6 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx |
| **Present bias** | -0,0045 | -0,0009 | 0,0121 | 0,0024 | -0,0048 | -0,0009 | 0,0235 | 0,0046 | | | | |
| | (0,06) | (0,013) | (0,061) | (0,012) | (0,068) | (0,013) | (0,067) | (0,013) | | | | |
| **Lossav** | -0,34** | -0,0724** | -0,2826** | -0,0563** | -0,2707* | -0,0502* | -0,3312** | -0,0651** | | | | |
| | (0,139) | (0,027) | (0,154) | (0,03) | (0,165) | (0,029) | (0,152) | (0,027) | | | | |
| **Riskav** | 0,2231 | 0,0475 | 0,2144 | 0,0427 | 0,326* | 0,0604* | 0,2682 | 0,0527 | | | | |
| | (0,138) | (0,028) | (0,155) | (0,029) | (0,197) | (0,033) | (0,166) | (0,03) | | | | |
| **Prud** | -0,0409 | -0,0087 | -0,0155 | -0,0031 | -0,1578 | -0,0293 | -0,1158 | -0,0228 | | | | |
| | (0,12) | (0,025) | (0,127) | (0,025) | (0,168) | (0,03) | (0,139) | (0,027) | | | | |
| **Temp** | 0,3917*** | 0,0834** | 0,4102*** | 0,0817*** | 0,4007*** | 0,0743*** | 0,376*** | 0,0739*** | | | | |
| | (0,119) | (0,021) | (0,129) | (0,021) | (0,134) | (0,02) | (0,126) | (0,021) | | | | |
| **Male** | | | -0,7070 | -0,1381 | -0,0923 | -0,0171 | | | 0,1405 | 0,0298 | | |
| | | | (0,541) | (0,101) | (0,642) | (0,119) | | | (0,605) | (0,128) | | |
| **Age** | | | 0,5799 | 0,1155 | 0,7819 | 0,1450 | | | 0,4923 | 0,1048 | | |
| | | | (0,497) | (0,096) | (0,788) | (0,141) | | | (0,52) | (0,109) | | |
| **Single** | | | -0,4746 | -0,0945 | -0,3308 | -0,0618 | | | -0,1454 | -0,0310 | | |
| | | | (0,454) | (0,089) | (0,474) | (0,089) | | | (0,388) | (0,083) | | |
| **Education** | | | -0,2070 | -0,0412 | -0,4298 | -0,0797 | | | -0,2530 | -0,0538 | | |
| | | | (0,328) | (0,065) | (0,347) | (0,063) | | | (0,316) | (0,067) | | |
| **Income** | | | -0,3470 | -0,0691 | -0,2202 | -0,0408 | | | -0,2623 | -0,0558 | | |
| | | | (0,248) | (0,047) | (0,254) | (0,046) | | | (0,251) | (0,052) | | |
| **Unemployment** | | | 0,6377 | 0,1305 | 0,9069* | 0,1725* | | | 0,9119* | 0,1985* | | |
| | | | (0,472) | (0,096) | (0,552) | (0,1) | | | (0,48) | (0,102) | | |
| **Extroversion** | | | | | -0,0011 | -0,0002 | -0,1268 | -0,0249 | 0,0146 | 0,0031 | -0,0815 | -0,0185 |
| | | | | | (0,168) | (0,031) | (0,149) | (0,029) | (0,136) | (0,029) | (0,122) | (0,027) |
| **Agreeableness** | | | | | 0,0703 | 0,0130 | 0,1318 | 0,0259 | 0,0783 | 0,0167 | 0,1491 | 0,0338 |
| | | | | | (0,125) | (0,023) | (0,12) | (0,024) | (0,122) | (0,026) | (0,114) | (0,026) |
| **Conscientiousness** | | | | | 0,0763 | 0,0141 | -0,0542 | -0,0106 | 0,0616 | 0,0131 | -0,0232 | -0,0053 |
| | | | | | (0,131) | (0,024) | (0,113) | (0,022) | (0,121) | (0,026) | (0,105) | (0,024) |
| **Neuroticism** | | | | | 0,2987* | 0,0554** | 0,1884** | 0,037** | 0,2429** | 0,0517*** | 0,1919** | 0,0435** |
| | | | | | (0,154) | (0,026) | (0,095) | (0,018) | (0,099) | (0,02) | (0,084) | (0,018) |
| **Openness** | | | | | 0,1981 | 0,0367 | 0,2107 | 0,0414 | 0,2567* | 0,0546* | 0,2315* | 0,0525* |
| | | | | | (0,164) | (0,031) | (0,144) | (0,028) | (0,15) | (0,031) | (0,129) | (0,028) |
| **Observations** | 143 | | 143 | | 143 | | 143 | | 143 | | 143 | |
| **Pseudo $R^2$** | 0,113 | | 0,1581 | | 0,2070 | | 0.1677 | | 0,1132 | | 0,0692 | |

*Robust standard errors in parentheses: *** p<0.01, **p<0.05, * p<0.1.*

## 6.6. Regression for Hypothesis 2 and 3

H 2: Crypto investors present lower loss aversion than general population.

H 3: Crypto investors present greater tolerance to risk exposure than general population.

Table 10 presents the results of the second regression, which correspond to hypotheses 2 and 3. The results of the second regression indicate that there are more significant differences between cryptocurrency investors and the general population than stock market population.

This result is consistent with the findings of Kumar (2009), Leuz et al. (2018), and Dorn Jones et al. (2015), who claim that due to the risky nature of cryptocurrency investments, they may attract the same types of investors as lottery stocks, penny stocks, and gamblers, as opposed to the general population. Logistic regression of economics preferences demonstrates that crypto investors are more likely to exhibit a lower present bias across all models, but none of them are statistically significant. In contrast, 1 unit of loss aversion is estimated to increase the probability of being a crypto investor compared to a non-investor by 0.009 percentage points at a significance level of 5% in a model that investigates only economic preferences. This result indicates that as participants' loss aversion increased, so did their attitude towards loss, as this variable is inverse to loss aversion and crypto investors are more likely to be less averse than the general population. Also, Benartzi and Thaler (1995) believe that people do not own stock due to loss aversion, hence same is for cryptocurrencies or other type of investments with volatile values. In addition, the second regression yields statistically significant findings for age, indicating that the younger crypto investors are, the less risk-averse they are. Numerous other studies support this point of view, as the possibility for loss associated with everyday decisions grows with age (Ebner et al., 2006; Depping and Freund, 2011; Mata and Hertwig, 2018; Lockenhoff, 2018). In general, cryptocurrency investors are risk-tolerant, more temperance, but not prudent compared to non-investors. In contrast to Eckel and Grossman (2008) and Groson and Gneezy (2009), who found that persons who are risk adverse tend to be more temperate and prudent, crypto investors are not prudent, despite the fact that they have increased probability of being less risk averse and less temperate. Holmen (2018) also indicate that the sample of financial professionals is substantially more risk tolerant than the overall population, I observe a similar trend, but it is not statistically significant.

Except for relationship status, education level, and unemployment, demographic variables exhibit significant differences in all categories. One unit of male is estimated to increase the probability of being a crypto investor relative to the general population by 0.39, 0.41, and 0.39 percentage points in models 2, 3, and 5, respectively, based on statistical evidence at the 1% level. This finding is consistent with Wan et al. (2005), Pijpers et al. (2001) and Hasso et al. (2019), who find that men have a greater propensity to adopt online and mobile banking than women, thus Dorn Jones, Dorn, and Sengmueller (2015) demonstrate that male, are more prone to gamble than other general population. In every model, younger individuals have a significantly higher probability of being crypto investors than the general population by

1 percent, Bohr and Bashir (2014), support this view. Similar to the increase in age, the increase in income presents an average of 0.10 percentage points more non-investors than crypto investors. Findings linked to income are contrary to Smyth (2013)'s investigations; nevertheless, the studies notably differ in their classification of income and age participants. While the average age of investors in my sample is 27, the average age of those previously investigated is 35. Moreover, Lammer (2020) indicates the income of bitcoin investors is much more than that of non-investors. Younger investors may be more tech-savvy and so invest directly in Bitcoins, whilst elderly investors find it more comfortable to participate in cryptocurrencies.

There is evidence, as shown in Table 10, that the scores for personal traits reveal significant differences between cryptocurrency investors and the general population. First, an increase in conscientiousness and openness increases the likelihood that a participant is a crypto investor by 0.05 and 0.10 percentage points at 10% and 1% level of significance respectively. In contrast, an increase in extroversion tends to be positive for the general population by 0.10 percent at a significance level of 1 percent. Agreeableness is associated with a decreased likelihood of being a crypto investor, whereas neuroticism is associated with an increased likelihood; however, neither of these claims is supported by statistical evidence. Extroversion and agreeableness are detrimental to investor and stock ownership, as found by Brown and Taylor (2014), who examine the relationship between the Big Five traits and the ownership of specific assets. Their findings are consistent with mine, which indicate that these traits are detrimental to investor and stock ownership. According to Bucciol et al. (2015) and Zarri (2017), agreeableness is also negatively associated with stock ownership. Lauriola and Levin also reveal connections between neuroticism and openness from the Big Five and the choice to take risks (2001). The only difference is that my results demonstrate that neuroticism has a positive effect on crypto investors. Last but not least, in 2002, Nicholson, Fenton, Soane, and Willman discovered that risk propensity was associated with high scores for extraversion and openness to experience and low scores for neuroticism, agreeableness, and conscientiousness. However, even if crypto investors are not significantly less risk averse than the general population, my results are completely at odds with their findings.

*Table 10. Regression results for 2nd and 3rd hypothesis*

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | | Model 6 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx | Logit Coef | Marginals dy/dx |
| **Present bias** | -0,1049 | -0,0152 | -0,1259 | -0,0131 | -0,0656 | -0,0049 | -0,0702 | -0,0083 | | | | |
| | (0,071) | (0,01) | (0,092) | (0,009) | (0,125) | (0,009) | (0,082) | (0,009) | | | | |
| **Lossav** | 0,4459* | 0,0647** | 0,0318 | 0,0033 | -0,1659 | -0,0124 | 0,5176* | 0,0613* | | | | |
| | (0,234) | (0,032) | -0,3430 | (0,035) | (0,411) | (0,032) | (0,283) | (0,033) | | | | |
| **Riskav** | 0,1207 | 0,0175 | 0,1905 | 0,0198 | 0,2915 | 0,0217 | 0,2792 | 0,0331 | | | | |
| | (0,22) | (0,031) | (0,303) | (0,03) | (0,382) | (0,029) | (0,236) | (0,025) | | | | |
| **Prud** | -0,0623 | -0,0090 | -0,1505 | -0,0157 | -0,1662 | -0,0124 | -0,2011 | -0,0238 | | | | |
| | (0,194) | (0,028) | (0,342) | (0,034) | (0,361) | (0,026) | (0,205) | (0,024) | | | | |
| **Temp** | 0,3130 | 0,0454 | 0,4502* | 0,0468* | 0,1740 | 0,0130 | 0,3106 | 0,0368 | | | | |
| | (0,205) | (0,028) | (0,276) | (0,025) | (0,257) | (0,019) | (0,235) | (0,026) | | | | |
| **Male** | | | 3,1877*** | 0,3958*** | 4,0841*** | 0,4146*** | | | 3,7299*** | 0,3955*** | | |
| | | | (1,097) | (0,094) | (1,192) | (0,083) | | | -1,1280 | (0,08) | | |
| **Age** | | | -1,9593*** | -0,2039*** | -3,5335*** | -0,2635*** | | | -3,4968*** | -0,2678*** | | |
| | | | (0,616) | (0,056) | (1,106) | (0,074) | | | -1,1220 | (0,052) | | |
| **Single** | | | 0,7330 | 0,0783 | 1,5402 | 0,1183 | | | 1,4302 | 0,1133 | | |
| | | | (0,93) | (0,092) | (1,068) | (0,068) | | | (1,034) | (0,071) | | |
| **Education** | | | 0,4965 | 0,0517 | 0,8547 | 0,0637 | | | 1,02* | 0,0781** | | |
| | | | (0,545) | (0,051) | (0,672) | (0,044) | | | (0,667) | (0,038) | | |
| **Income** | | | 1,0315* | 0,1073** | 1,1732* | 0,0875** | | | 1,3106* | 0,1004** | | |
| | | | (0,602) | (0,055) | (0,653) | (0,042) | | | (0,759) | (0,049) | | |
| **Unemployment** | | | 0,7643 | 0,0784 | 0,4342 | 0,0321 | | | 0,4067 | 0,0309 | | |
| | | | (0,843) | (0,089) | (1,12) | (0,083) | | | (0,946) | (0,073) | | |
| **Extroversion** | | | | | -1,3678*** | -0,102*** | -0,8148** | -0,0965** | -1,369*** | -0,1049*** | -0,7479** | -0,1047*** |
| | | | | | (0,346) | (0,024) | (0,375) | (0,038) | (0,384) | (0,02) | (0,301) | (0,035) |
| **Agreeableness** | | | | | -0,1211 | -0,0090 | -0,0872 | -0,0103 | -0,0515 | -0,0039 | 0,0419 | 0,0059 |
| | | | | | (0,288) | (0,022) | (0,183) | (0,022) | (0,265) | (0,02) | (0,184) | (0,026) |
| **Conscientiousness** | | | | | 0,7202** | 0,0537*** | 0,6062* | 0,0718** | 0,6339*** | 0,0486*** | 0,3551 | 0,0497* |
| | | | | | (0,306) | (0,02) | (0,318) | (0,028) | (0,247) | (0,017) | (0,233) | (0,029) |
| **Neuroticism** | | | | | 0,1882 | 0,0140 | 0,2228 | 0,0264 | 0,0755 | 0,0058 | 0,1158 | 0,0162 |
| | | | | | (0,308) | (0,024) | (0,142) | (0,018) | (0,24) | (0,019) | (0,125) | (0,018) |
| **Openness** | | | | | 1,1174*** | 0,0833*** | 0,4128* | 0,0489* | 1,2777* | 0,0979*** | 0,6912** | 0,0967*** |
| | | | | | (0,325) | (0,022) | (0,245) | (0,027) | (0,395) | (0,024) | (0,31) | (0,037) |
| **Observations** | 94 | | 94 | | 94 | | 94 | | 94 | | 94 | |
| **Pseudo $R^2$** | 0,1307 | | 0,3512 | | 0,5256 | | 0,2629 | | 0,5108 | | 0,1535 | |

*Robust standard errors in parentheses: *** p<0.01, **p<0.05, * p<0.1.*

## 7. Conclusion

This thesis examines the rising popularity of cryptocurrency investors in comparison to stock market investors and the general public based on their economic preferences, demography, and personal traits. My findings reveal two perspectives in separate fields. First-time crypto investors have a higher loss aversion but are also riskier than stock market participants. They have demographic disparities, but virtually all of them are empirically insignificant, and investors with high levels of neuroticism and openness tend to have an optimistic outlook to cryptocurrencies. Lastly, I demonstrate that Cryptocurrencies are becoming increasingly popular among young males with low loss aversion, rising income, low levels of extroversion, and high levels of conscientiousness and openness. These individuals are more inclined to invest in cryptocurrencies.

The available survey data impose several restrictions on this investigation. Importantly, the sample size of 163 respondents, of whom 74 are cryptocurrency investors, 69 are stock market investors, and 20 are from the general public, is rather small. Additionally, a time-consuming survey with little incentive and so many variables may be overly affected by outliers. They should thus be regarded with caution and supported by more study. All polls are limited by the fact that not everyone tells the truth. Even if the replies are anonymous, investors may choose not to divulge their economic preferences and personal characteristics in order to safeguard their identity.

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## 9. Appendix

**Survey**

Welcome to the survey!
Your answers will remain completely anonymous and confidential. The data will be destroyed after completion of the graduation process.

The survey takes about 8-13 minutes. Your participation in this survey is voluntary. You have the right to withdraw at any time during the study. For questions related to this survey, you can contact v.natsis@students.uu.nl.

By clicking the button below, you acknowledge:

• Voluntary participation in the study.
• Being 18 years of age or older.
• Being aware that you may choose to terminate your participation at any time for any reason

1. **Gender:**
   Female
   Male
   Other

2. **Age group:**
   Under 18
   18-24 years
   25-34 years
   35-44 years
   45-54 years
   55-64 years
   65-74 years
   75 years or older

3. **Relationship status:**
   Single
   Married or domestic partnership
   Widowed
   Divorced

4. **Education:**
   No education
   Elementary
   Lower secondary school
   High school
   Bachelors or equivalent

Masters or equivalent

Doctoral or equivalent

5. **Income:**

   No income

   €1 to €999

   €1,000 to €2,499

   €2,500 to €5,000

   Over €5,000

6. **Employment status:**

   Unemployed

   Part-time

   Full time

   Self-employed/ Freelancer

**Have you ever made any financial investment?**

**( )** stock market ( ) cryptocurrency ( ) No

**IF you have not made any investment decision, do you have any intention for future investments of the following areas?**

**( )** stock market ( ) cryptocurrency ( ) No

**Block 1**

Suppose you were given the choice between receiving a payment today or a payment in 12 months. We will now present to you some situations. The payment today is the same in each of these situations. The payment in 12 months is different in every situation. For each of these situations we would like to know which one you would choose. Please assume there is no inflation, i.e., future prices are the same as today's prices. Please consider the following: Would you rather receive amount 100€ today or y in 12 months?

Would you rather receive amount 100€ today or in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 110€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 120€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 130€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 140€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 150€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 160€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 170€ in 12 months?

(if they choose later, next c block)

Would you rather receive amount 100€ today or 180€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 190€ in 12 months?

(if they choose later, next block)

Would you rather receive amount 100€ today or 200€ in 12 months?

**Block 2**

Here is a game, suppose you were given the choice to participate in a lottery game. Will you accept or reject the following choices?

If the coin turns up head, you lose 2€; if the coin turns up tail you win 6€

Accept or Reject

(if they choose reject, next block)

If the coin turns up head, you lose 3€; if the coin turns up tail you win 6€

(if they choose reject, next block)

If the coin turns up head, you lose 4€; if the coin turns up tail you win 6€

(if they choose reject, next block)

If the coin turns up head, you lose 5€; if the coin turns up tail you win 6€

(if they choose reject, next block)

If the coin turns up head, you lose 6€; if the coin turns up tail you win 6€

(if they choose reject, next block)

If the coin turns up head, you lose 7€; if the coin turns up tail you win 6€

(if they choose reject, next block)

**Block 3**

**For risk aversion 5 choice task**

Left Lottery vs Right Lottery

20 vs 65 or 5,

25 vs 65 or 5,

30 vs 65 or 5,

35 vs 65 or 5,

40 vs 65 or 5

**For Prudence 5 choice task**

90 + [20, -20], 60 vs 90, 60+ [20, -20]

90 + [10, -10], 60 vs 90, 60+ [10, -10]

90 + [40, -40], 60 vs 90, 60+ [40, -40]

135 + [30, -30], 90 vs 135, 90+ [30, -30]

65 + [20, -20], 35 vs 65, 35+ [20, -20]

**For Temperance 5 choice task**

90+ [ 30, -30], 90+ [30, -30] vs 90, 90+ [30, -30] + [30, -30]

90+ [ 30, -30], 90+ [10, -10] vs 90, 90+ [30, -30] + [10, -10]

90+ [ 30, -30], 90+ [50, -50] vs 90, 90+ [30, -30] + [50, -50]

30+ [ 10, -10], 30+ [10, -10] vs 30, 30+ [10, -10] + [10, -10]

70+ [ 30, -30], 70+ [30, -30] vs 70, 70+ [30, -30] + [30, -30]

**Block 4**

The following statements concern your perception about yourself in a variety of situations. Your task is to indicate the numerical option that best expresses your opinion about yourself in each of the statements below. There are no "right" or "wrong" answers, just choose the number that you think best reflects yourself on each statement. Evaluate each statement carefully.

To do this, use the following range of responses:

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| I totally disagree | Disagree in part | Neither agree nor disagree | I agree in part | I totally agree |

I see myself as someone who is outgoing and sociable

I see myself as someone who is reserved

I see myself as someone who is generally trusting

I see myself as someone who tends to find fault with others

I see myself as someone who does a thorough job

I see myself as someone who tends to be lazy

I see myself as someone who gets nervous easily

I see myself as someone who is relaxed and handles stress well

I see myself as someone who has an active imagination

I see myself as someone who has few artistic interest